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Long-term energy-system optimization models

Capturing the challenges of integrating intermittent renewable energy sources and assessing the suitability for descriptive scenario analyses

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Dissertation presented in partial fulfillment of the requirements for the degree of Doctor of Engineering Science (PhD): Mechanical Engineering

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Preface - Dankwoord

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Abstract

This dissertation focuses on energy-system optimization models (ESOMs). These models are used to generate possible transition pathways of the entire energy system in a single or multiple countries over a time horizon of multiple decades. Experimenting with different transition pathways allows gaining insights into the complexity of the energy system transition and can help in forming a long-term vision of this transition. In addition, these transition pathways can be used to evaluate the adequacy of the current policy framework to achieve a desired transition. As such, these models form valuable tools for policy makers.

Due to the large scope of ESOMs, solving these models quickly becomes computationally demanding. To limit the computational cost, ESOMs have historically used a low level of temporal and technical detail to represent the operation of the power system, i.e., intra-annual variations in demand and renewable generation are typically represented by 4-48 so-called time slices and the technical constraints faced by thermal power plants when changing their power output, starting up or shutting down are neglected. However, in the context of an increasing penetration of strongly fluctuating and limitedly predictable renewable energy sources such as wind turbines and solar PV panels, this low level of temporal and technical detail might not be sufficient to grasp the challenges related to integrating these intermittent renewable energy sources (IRES).

In this regard, a first objective of this dissertation is to assess the impact of this low level of temporal and technical detail on the results provided by ESOMs. The presented research indicates that both the low level of temporal and technical detail lead to an overestimation of the uptake of IRES, an overestimation of the electricity that can be generated by baseload technologies and an underestimation of the system costs. As the penetration of IRES increases, particularly the low level of temporal detail starts to have a significant impact on the obtained results. This is shown to result from the fact that traditional time-slicing methods lead to smoothing of the variability of IRES.

A resulting second objective is to develop improved time-slicing methods. In this regard, two time-slicing methods are proposed which are shown to better capture the variability of IRES without necessitating an increase in the number of time slices. This dissertation focuses in depth on one time-slicing method which relies on representing the different conditions occurring throughout a year via a small number of representative historical periods (e.g., days). The selection of the representative set of historical periods is key for the accuracy of this method. In this regard, a novel, optimization-based, approach to select a representative set of historical periods is developed and benchmarked to state-of-the-art approaches available in the literature. This developed approach is shown to achieve better results than the approaches available in the literature. The significance is that, given that a limited number of time slices can be used, a better selection of representative periods allows improving the results provided by ESOMs.

A third objective is to develop methods to tractably account for technical constraints in ESOMs. To this end, reduced formulations of the technical constraints faced by power plants are formulated. The results of a planning model integrating these reduced formulations are compared to the results of a planning model which integrates detailed clustered unit commitment (CUC) constraints for a variety of scenarios and cases. This analysis shows that the developed reduced formulations are sufficiently accurate for long-term planning purposes while reducing computation time by a factor of 5-600 with respect to the model with integrated CUC constraints. However, the research presented in this dissertation also highlights that, due to assumptions which need to be made regarding the cycling capabilities of thermal power plants and the requirements for operating reserves, there is a risk that the incorporated technical constraints are overly and unrealistically restrictive, which can lead to strong overestimations of the system costs and suboptimally low penetration levels of IRES. Recommendations to avoid this potential pitfall are presented.

The final part of this dissertation relates to the fact that since the liberalization of the electricity markets, investment decisions in generation capacity are made by private, profit-maximizing, actors. The decisions made by these actors can be influenced by the market design and the policy framework. In this regard, the last objective of this dissertation is to determine to what extent ESOMs can account for specific market designs, policy interventions and behavioral characteristics. An analysis is presented which shows that a number of inherent assumptions are made in optimization models which prevent from representing certain market designs, policy interventions as well as behavioral characteristics.

Beknopte samenvatting

Dit proefschrift handelt over energiesysteemoptimalisatiemodellen (ESOM's). Deze modellen worden gebruikt om mogelijke transitiepaden voor het energiesysteem van één of meerdere landen over een tijdshorizon van tientallen jaren te genereren. Door meerdere van deze transitiepaden te gaan analyseren kunnen inzichten verworven worden en kan er een lange-termijn visie over de gewenste transitie van het energiesysteem ontwikkeld worden. Naast het vormen van zo een visie over de gewenste energietransitie laten deze ESOM's ook toe om te analyseren of een portfolio van beleidsmaatregelen toereikend is om bepaalde doelstellingen ook effectief te realiseren. Deze modellen vormen dan ook een waardevol gereedschap om energiebeleid te vormen en te ondersteunen.

Het oplossen en uitrekenen van deze ESOM's vereist veel rekenkracht. Om de computationele kosten voldoende laag te houden worden bepaalde operationele aspecten van het balanceren van het elektriciteitssysteem sterk vereenvoudigd gemodelleerd: intra jaarlijkse variaties in de vraag naar elektriciteit en de hernieuwbare productie worden typisch voorgesteld door middel van slechts 4-48 tijdssegmenten, en de technische beperkingen die thermische elektriciteitscentrales ondervinden bij het opstarten, afsluiten of het veranderen van de productie worden typisch verwaarloosd. In het licht van een steeds toenemende hoeveelheid sterk fluctuerende en beperkt voorspelbare elektriciteitsproductie door hernieuwbare energiebronnen, zoals wind turbines en zonnepanelen, zouden deze vereenvoudigingen te sterk kunnen zijn om accuraat de uitdagingen die gepaard gaan aan het op grote schaal integreren van zulke intermitterende hernieuwbare energiebronnen (IHEB's) te reflecteren.

Het eerste doel van dit proefschrift is de impact van deze vereenvoudigingen op de door ESOM's bekomen resultaten in te schatten. Dit proefschrift toont aan dat zowel de lage tijdsresolutie als de verwaarlozing van technische beperkingen van elektriciteitscentrales leiden tot een overschatting van de opname van IHEB's, een overschatting van de elektriciteitsproductie door middel van basislastcentrales en een onderschatting van de kost. Er wordt bovendien

aangetoond dat voor systemen met een groot aandeel aan IHEB's de lage tijdsresolutie de grootste impact heeft op de resultaten. Dit is het gevolg van het feit dat de traditionele methodes om een jaar te karakteriseren via tijdssegmenten de variabele elektriciteitsproductie door IHEB's sterk afvlakken.

Het tweede doel is het ontwikkelen van verbeterde methodes om een jaar voor te stellen in een beperkt aantal tijdssegmenten. Dit proefschrift stelt twee methodes voor en toont aan dat beide voorgestelde methodes beter de variabiliteit van IHEB's voorstellen zonder een nood aan het gebruik van een groter aantal tijdssegmenten. Er wordt dieper ingegaan op één methode in het bijzonder die de variaties binnen een jaar probeert voor te stellen door middel van de data van een klein aantal representatieve historische periodes (bv. dagen). Hierbij is het selecteren van de historische periodes cruciaal. Een nieuwe manier om door middel van een optimalisatiemodel een set van representatieve historische periodes te selecteren is ontwikkeld. De performantie van deze methode wordt vergeleken met state-of-the-art methodes uit de literatuur, en er wordt aangetoond dat de ontwikkelde methode betere resultaten behaalt. Het belang hiervan is dat een betere selectie van een set van representatieve periodes toelaat de accuraatheid van ESOM's te verbeteren zonder een toename van de rekentijd.

Het derde doel is het ontwikkelen van een manier om de technische beperkingen te modelleren zonder de rekenkracht sterk te laten toenemen. Hiertoe zijn gereduceerde formuleringen van de wiskundige uitdrukkingen die de technische beperkingen van centrales voorstellen ontwikkeld. Er wordt aangetoond dat deze gereduceerde formuleringen voldoende accuraat zijn voor de beoogde toepassing en de rekentijd met een factor 5-600 kunnen verkleinen ten opzichte van een model dat gedetailleerde technische beperkingen beschouwt. Het onderzoek vestigt de aandacht verder op het risico dat, door de noodzaak aan het maken van aannames over de flexibiliteit van thermische centrales en de dimensionering van reserves, de technische beperkingen overmatig en onrealistisch restrictief kunnen zijn. Dit kan dan leiden tot een sterke overschatting van de systeemkost en een foute inschatting van de optimale hoeveelheid IHEB's. Aanbevelingen worden gedaan om deze valkuil te voorkomen.

Het laatste doel van dit proefschrift is het bepalen van de beperkingen van ESOM's om specifieke markten, beleidsmaatregelen en het beslissingsgedrag van marktspelers voor te kunnen stellen. Dit laatste doel kader in de context van geliberaliseerde elektriciteitsmarkten, waarin investeringsbeslissingen in productiecapaciteit gedaan worden door private, winstmaximaliserende, spelers. Er wordt aangetoond dat optimalisatiemodellen inherent een aantal aannames maken die het onmogelijk maken om bepaalde marktontwerpen, beleidsmaatregelen of beslissingsgedrag, en de impact daarvan op het marktevenwicht, voor te stellen.

List of Abbreviations

BESS battery energy storage systems

CA clustering algorithm

CCGT combined cycle gas turbine

CE correlation error

CGE computable general equilibrum

CHP combined heat and power

COAL SC supercritical pulverized coal-fired power plant

CS consumer surplus

CUC clustered unit commitment

DC duration curve

DSO distribution system operator

ED economic dispatch

EI enhanced integral

EPEC equilibrium problem with equilibrium constraints

ESOM energy-system optimization model

ETS emission trading scheme

EU European Union

FOM fixed operations and maintenance

GenCo generation company

GHG greenhouse gas

IAM integrated assessment model

IRES intermittent renewable energy sources

KKT Karush-Kuhn-Tucker

LDC load duration curve

LP linear programming

MCP mixed complementarity problem

MILP mixed integer linear programming

MO merit order

MPEC mathematical problem with equilibrium constraints

MSOP minimum stable operating point

MUDT minimum up and down time

NRMSE normalized root-mean-square error

NUC nuclear power plant

OCGT open cycle gas turbine

PHS pumped hydro storage

PLEL part-load efficiency losses

PS producer surplus

PSOM power-system optimization model

PV photovoltaic

RDC ramp duration curve

REE relative energy error

RES renewable energy sources

RLDC residual load duration curve

RMSE root-mean-square error

RS random selection

SC start-up costs

SD semi-dynamic

TS total surplus

TSO transmission system operator

UC unit commitment

VOM variable operations and maintenance

VRFER variable renewable forecast error reserves

Nomenclature

CH4: Optimization model for selecting representative historical periods

Sets

$b \in \mathcal{B}$	Bins
$c \in \mathcal{C}$	Duration curves that need to be approximated
$d \in \mathcal{D}$	Potential representative historical periods (days)

Parameters

$A_{c,b,d}$	Share of the time of potential representative period (day) d during which the time series corresponding to duration curve c exceeds the lowest value corresponding to bin b	*[%]*
$L_{c,b}$	Share of the time during which duration curve c exceeds the lowest value corresponding to bin b	*[%]*
N_{repr}	Number of representative periods (days) to select	*[-]*
N_{total}	Total number of times a single representative period (day) needs to be repeated to scale to a year	*[-]*

Decision Variables

$error_{c,b}$	Error made in approximating duration curve c near the lowest value of the range corresponding to bin b	*[-]*
u_d	Binary variable indicating whether potential representative period (day) d is selected	*[-]*

w_d	Weight assigned to representative period (day) d	*[-]*

CH5: Greenfield power-system optimization model with integrated clustered unit commitment constraints

Sets

$g \in \mathcal{G}$	Set of generation technologies g
$gd \in \mathcal{GD}$	Set of dispatchable generation technologies gd
$gr \in \mathcal{GR}$	Set of intermittent renewable generation technologies gr
$p \in \mathcal{P}$	Set of representative historical periods p
$r \in \mathcal{R}$	Set of operating reserve categories r
$s \in \mathcal{S}$	Set of storage technologies s
$sm \in \mathcal{SM}$	Set of pumped hydro storage technologies sm
$ss \in \mathcal{SS}$	Set of battery storage technologies ss
$t \in \mathcal{T}$	Set of time steps t within each historical period

Parameters

$\overline{D}$	Annual peak demand for electrical power	*[MW]*
$D_{p,t}$	Demand for electrical power	*[MW]*
C_{gd}^{RAMP}	Ramping cost	$[€/(\Delta MW)]$
C_{gd}^{SU}	Start-up cost	$[€/(\Delta MW)]$
$C_{g/s}^{VOM}$	Variable operations and maintenance cost	*[€/MWh]*
$C_{g/s}^{FOM}$	Fixed operations and maintenance cost	*[€/(MW.a)]*
C_{g}^{INV}	Annualized investment cost	*[€/(MW.a)]*
$C_{s}^{INV,CAP}$	Annualized investment cost for charging and discharging capacity of storage technologies	*[€/(MW.a)]*
$C_{s}^{INV,EN}$	Annualized investment cost for energy reservoir of storage technologies	*[€/(MW.a)]*
$AF_{gd/s}$	Availability factor	*[-]*
MDT_{gd}	Minimum down time	*[h]*
SU_{gd}	Maximum power of plant starting up	*[MW]*
$SUT_{gd/sm}$	Time required for starting up	*[h]*
$SDT_{gd/sm}$	Time required for shutting down	*[h]*
η_s	Round-trip efficiency	*[-]*
R_{gd}	Ramp rate	$[\%\overline{P}_{gd}/h]$

$\underline{P}_{gd}$	Minimum operating point	*[MW]*
SD_{gd}	Maximum power of plant shutting down	*[MW]*
MC_{gd}	Marginal fuel and emission cost	*[€/MWh]*
$\overline{P}_{gd}$	Maximum operating point	*[MW]*
MUT_{gd}	Minimum up time	*[h]*
NC_{gd}	Generation cost at minimum power output	*[€/h]*
$CF_{gr,p,t}$	Capacity factor	*[-]*
T^{GHG}	Tax for greenhouse gas emissions	*[€/$ton^{CO_2^{eq}}$]*
$VOLR$	Penalty for shedding of operating reserves	*[€/MW h]*
S	Support for renewable electricity generation	*[MW]*
$VOLL$	Penalty for load shedding	*[€/MWh]*
PM	Planning reserve margin	*[-]*
$R^{FE}_{r,gr}$	Share of scheduled intermittent generation for which operating reserves are required	*[-]*
T^{DUR}_{r}	Duration that storage technologies are required to be able to provide reserves	*[h]*
R^{DEM}_{r}	Share of demand for which operating reserves are required	*[-]*
S^{SPIN}_{r}	Minimum share of spinning reserves	*[-]*
T^{ACT}_{r}	Required activation time for operating reserve	*[h]*
$\underline{P}^{C}_{sm}$	Minimum operating point while charging	*[MW]*
$\overline{DUR}_s$	Maximum energy reservoir capacity relative to rated electrical power	*[h]*
$\underline{DUR}_s$	Minimum energy reservoir capacity relative to rated electrical power	*[h]*
$\underline{P}^{D}_{sm}$	Minimum operating point while discharging	*[MW]*
W_p	Number of times representative period p is repeated within one year	*[-]*
Δ_t	Duration of time step t	*[h]*

Decision Variables

c^{ramp}	Annual ramping costs	*[€]*
c^{fom}	Annual fixed operations and maintenance cost	*[€]*
c^{inv}	Annual investment cost	*[€]*
v^{ires}	Annual support for renewable electricity generation	*[€]*
c^{lr}	Annual reserve-shedding costs	*[€]*
c^{ll}	Annual load-shedding costs	*[€]*
c^{su}	Annual start-up costs	*[€]*

c^{gen}	Annual generation costs	*[€]*
c^{vom}	Annual variable operations and maintenance cost	*[€]*
$n^{sd}_{gd,p,t}$	Number of units shutting down	*[-]*
$n^{su}_{gd,p,t}$	Number of units starting up	*[-]*
$n^{on}_{gd,p,t}$	Number of online units	*[-]*
n^{av}_{gd}	Number of available units	*[-]*
$ramp_{gd,p,t}$	Change in electrical power output	*[MW]*
$g_{gd,p,t}$	Electrical power generation above the minimum operating point	*[MW]*
cap_g	Installed capacity	*[MW]*
cap^{av}_{gd}	Available capacity	*[MW]*
$gen_{g,p,t}$	Electrical power generation	*[MW]*
$ll_{p,t}$	Unserved demand	*[MW]*
$gen^{certain}_{gr,p,t}$	IRES generation that can be guaranteed with a reasonable certainty	*[MW]*
$curt_{gr,p,t}$	Curtailment of renewable electricity generation	*[MW]*
$gen^{uncertain}_{gr,p,t}$	IRES generation above the value that can be guaranteed with a reasonable certainty	*[MW]*
$z_{gr,p,t}$	Binary variable indicating whether IRES can provide upward reserves	*[MW]*
$y_{gr,p,t}$	Binary variable indicating whether the IRES generation level is below the level that can be guaranteed with a reasonable certainty	*[MW]*
$r^{+}_{r,gd,p,t}$	Upward reserves procured	*[MW]*
$r^{+,spin}_{r,gd,p,t}$	Spinning upward reserves procured	*[MW]*
$r^{+,ns}_{r,gd,p,t}$	Non-spinning upward reserves procured	*[MW]*
$n^{+,ns}_{gd,p,t}$	Number of units procured to start-up for providing upward reserves	*[-]*
$lr_{r,p,t}$	Unprovided operating reserves	*[MW]*
cap^{av}_{s}	Available charging/discharging power capacity	*[MW]*
cap^{e}_{s}	Installed energy reservoir capacity	*[MWh]*
cap_s	Installed charging/discharging power capacity	*[MW]*
$e^{f}_{s,p,t}$	Energy content of storage at in the first repitition of the representative period	*[MWh]*
$p^{d}_{s,p,t}$	Electrical power output while discharging	*[MW]*
$p^{c}_{s,p,t}$	Electrical power consumption while charging	*[MW]*
$e^{l}_{s,p,t}$	Energy content of storage at in the last repitition of the representative period	*[MWh]*
$n^{d,su}_{sm,p,t}$	Number of units starting up to discharge	*[-]*
$n^{c,av}_{sm,p,t}$	Number of available units for charging	*[-]*

$n^{c,on}_{sm,p,t}$	Number of online charging units	*[-]*
$n^{c,su}_{sm,p,t}$	Number of units starting up to charge	*[-]*
$n^{c,sd}_{sm,p,t}$	Number of charging units shutting down	*[-]*
$n^{d,av}_{sm,p,t}$	Number of available units for discharging	*[-]*
$n^{d,on}_{sm,p,t}$	Number of online discharging units	*[-]*
$n^{d,sd}_{sm,p,t}$	Number of discharging units shutting down	*[-]*
$r^{+}_{r,s,p,t}$	Upward reserves procured from storage technologies	*[MW]*
$r^{+,c}_{r,s,p,t}$	Upward reserves procured from storage technologies by adapting charging output	*[MW]*
$r^{+,d}_{r,s,p,t}$	Upward reserves procured from storage technologies by adapting discharging output	*[MW]*
$r^{+,spin,c}_{r,sm,p,t}$	Spinning upward reserves procured from pumped hydro storage technologies while charging	*[MW]*
$r^{+,spin,d}_{r,sm,p,t}$	Spinning upward reserves procured from pumped hydro storage technologies while discharging	*[MW]*
$r^{+,ns,d}_{r,sm,p,t}$	Non-spinning upward reserves procured from pumped hydro storage technologies by starting up turbining units	*[MW]*
$r^{+,ns,c}_{r,sm,p,t}$	Non-spinning upward reserves procured from pumped hydro storage technologies by shutting down pumping units	*[MW]*
$n^{+,sd,c}_{sm,p,t}$	Number of units procured to shut down charging for providing upward reserves	*[-]*
$n^{+,su,d}_{sm,p,t}$	Number of units procured to start-up discharging for providing upward reserves	*[-]*

Contents

Chapter 1

Introduction

This chapter introduces the research presented in this dissertation. First, Section 1.1 sketches the context in which the research is embedded. Next, the problem statement and the corresponding motivation for the research are presented in Section 1.2. The objectives and scope of the research are discussed in Section 1.3. To end, an outline for the remainder of the dissertation is presented in Section 1.4.

1.1 Context

The energy system and especially the electricity system in Europe are undergoing drastic changes. Two changes in particular form the context of the research presented in this PhD dissertation. These are (i) the increasing penetration of IRES and (ii) the liberalization and deregulation of the electricity markets.

1.1.1 Increasing penetration of intermittent renewable energy sources

Driven by concerns for global warming, the European Union (EU) has set ambitious targets for the reduction of greenhouse gas (GHG) emissions. Towards 2020, the 2020 climate and energy package [1] sets three key targets: reducing GHG emissions by 20% with respect to 1990 levels, obtaining 20% of EU end energy from renewable energy sources (RES) and improving energy efficiency by 20% compared to a set baseline. The more recent climate and energy framework

[2] builds on the 2020 climate and energy package and specifies the targets towards 2030. These targets include the reduction of GHG emissions by at least 40% with respect to 1990 levels, and a further increase of the share of renewable end energy up to at least 27%. These targets are in line with the longer term perspective presented in the Energy Roadmap 2050. On this 2050 timeframe, the EU commits itself to reducing GHG emissions to 80-95% below 1990 levels [3]. Several possible pathways to achieve this level of decarbonization have been analyzed. In all considered pathways, the electricity sector is projected to play a key role, with GHG emission reductions in the electricity sector projected to be in the range of 93-99% by 2050 (with respect to 1990 levels). In addition, also the decarbonization of heating and transportation strongly relies on a shift towards electric heat pumps and electric vehicles. Regarding the share of RES in the electricity sector, this would increase up to 64-97% by 2050 depending on the specific transition pathways [4].

Some of these RES, such as wind power generation and solar photovoltaic (PV) power generation, have an intermittent character, i.e., they are highly variable and limitedly predictable. This is due to the fact that the electrical output of these IRES is strongly dependent on the weather conditions. In the absence of a cheap way of storing large amounts of electrical energy, the demand and supply of electricity must be in balance at all times. Therefore, a large penetration of IRES can have a significant impact on the operation of the electric power system. First, the variability of IRES generation increases the need for cycling of dispatchable power plants (i.e., changing the electrical power output by ramping up/down or by switching on/off) [5, 6]. Indeed, whenever there is a decline/increase in the electrical power generated by IRES, some of the conventional power plants, such as nuclear, coal-fired or gas-fired power plants, must increase/decrease their power output instantaneously. The increased cycling imposes additional costs for the system, which consists of additional consumption of primary fuels during start-ups and part-load operation, on the one hand, and increased capital, maintenance and opportunity costs due to increased wear and tear of components, on the other hand [7]. In addition, the cycling capabilities of tradtional thermal power plants are limited. As the share of IRES increases, power plants might be pushed against their operational constraints (e.g., limited rates at which the power output can be increased/decreased, minimal duration for which power plants must remain online/offline after a startup/shutdown, etc.) [8]. As a result, these technical constraints can cause a shift from baseload generation towards more expensive, but more flexible mid/peak load generation. Alternatively, other sources of flexibility, such as electrical energy storage technologies (ESS) or active demand response (ADR) can be deployed to maintain the balance between supply and demand. Second, sufficient back-up capacity is needed to deal with periods in which IRES output is low. Third, the limited predictability of IRES generation leads to an increased demand for operating reserves to deal with forecast errors [9, 10, 11].

1.1.2 Liberalization and deregulation of European electricity markets

A second change relevant for this dissertation is the transition from utilities which had a geographical monopoly over the generation, transmission, distribution and supply of electricity to a deregulated market setting in which multiple electricity generation companies and retailers compete for the provision and supply of electricity. Up to the 1990s, in most European countries or regions, a single, vertically integrated, utility was responsible for the generation, transmission, distribution and the supply of electricity. These vertically integrated utilities were either public companies or regulated private companies. However, economists argued that competitive markets would provide better incentives for an efficient operation of the power system and appropriate investment decisions which should ultimately lead to lower prices for consumers. For these reasons, a gradual process of liberalization started in the EU in the 1990s [12]. In essence, this process involved the unbundling of generation and retail activities from transmission and distribution activities, the introduction of competitive markets for generation and supply (retail) of electricity, the introduction of natural monopolies for transmission and distribution, and the introduction of an independent regulator in charge of monitoring both the market-activities (generation and supply) and the regulated activities (transmission and distribution) [13, 14].

In such an unbundled setting, investments in generation capacity are to be made by private generation companies which aim to maximize their profits. These generation companies face a significant amount of uncertainty regarding the return on investment which stems from the uncertainty regarding future demand, fuel costs, technological evolution, policy interventions, technological acceptance as well as the investment decisions that will be made by competing generation companies [15]. In addition, the recent feed-in of renewable energy induced by different support mechanisms has reduced the number of operating hours of dispatchable power plants and at the same time reduced wholesale electricity prices [16]. As a result, little investments in dispatchable power plants have recently been observed which has led to concerns regarding generation adequacy in some regional markets. In this regard, there is an ongoing debate on whether energy-only markets provide the incentives for sufficient investments or whether they should be complemented by so-called capacity remuneration mechanisms (see e.g., [17, 18, 19]). At the same time, a similar debate is ongoing on how to design the markets to properly remunerate the required flexibility (see e.g., [20, 21, 22, 23]). These ongoing discussions highlight the fact that in a deregulated market setting, the market design as well as policy interventions strongly impact the investment decisions of private generation companies.

1.2 Motivation

1.2.1 Long-term energy-system planning models

For analyzing possible transition pathways for the decarbonization of the energy system, long-term energy-system planning models are frequently used. Such models generate consistent pathways for the transition of all energy sectors (including the electrical power sector, heating, transportation, etc.) for a single or multiple countries over a horizon of multiple decades (e.g., up to 2050). As such, these models consider the complex inter-temporal, inter-sectoral and inter-regional relationships and allow improving our understanding of the energy transition. Frequently, these models are formulated as optimization models, where the objective is to minimize the total system cost for the provision of different energy services (see e.g., MARKAL/TIMES models [24, 25] or the MESSAGE model [26]). For this reason, these models are referred to as energy-system optimization models (ESOMs). In terms of the required input, four categories can be distinguished: the demand for energy services, primary fuel prices, technology descriptions (including their costs) and a policy framework. The output of these models is a description of the transition pathway which comprises information about investments in different technologies, on how these technologies are operated and about the associated costs and emissions.

Long-term energy-system planning models form valuable tools for policy making. In this regard, a number of distinct scenarios (possible transition pathways) are typically created and compared. Depending on the question that needs to be addressed, different types of scenario exercises can be performed. One can distinguish between normative/prescriptive scenarios and descriptive scenarios. In normative or prescriptive scenarios, certain boundary conditions of a desired future state of the energy system are imposed upon the model and one is interested in determining the optimal pathway towards this future state [27, 28]. A typical example is when a certain target for the share of RES is imposed and the questions that one wants to answer have a normative character, e.g., which energy sectors should decarbonize first, which technologies are essential for achieving the target cost effectively, etc.). As such, normative scenarios provide information about the ideal transition of an energy system (how do we want the energy system to evolve?) towards the stated objective (or "norm"). Descriptive scenarios, on the other hand, do not impose a desired future state, but rather aim to describe a likely evolution of the energy system, i.e., given certain assumptions on fuel prices, technology cost evolutions and policy interventions, how do we expect the energy system to evolve. Such scenarios can be used to evaluate whether certain policy measures could achieve the desired state, and if so, under which conditions [29]. For instance, policy-makers could decide to implement a subsidy scheme for solar PV panels and wind turbines with the idea of reaching a certain target for the share of RES, but without imposing the target itself. A descriptive scenario would then allow assessing whether this measure is sufficient to achieve the desired GHG emission reduction targets and what the environmental, social and economic implications of these policy measures would be. Such descriptive scenarios are therefore crucial for translating the visions (how do we want the energy system to evolve?) which can be created using normative scenarios, to a specific policy portfolio (how will we make sure that the desired transition will effectively be realized?).

In recent years, multiple studies have developed and analyzed scenarios for the evolution towards a sustainable energy system, either focusing on the feasibility and implications of realizing ambitious targets for renewable energy or the reduction of GHG emissions (e.g., [30, 31, 32]), the role of specific technologies (e.g., [33, 34, 35]) or the role of policy instruments (e.g., [36, 37]). In addition to such academic studies, planning models have been regularly deployed for providing direct policy support. In Europe, the PRIMES model [38] in particular has been used frequently for developing EU policy [39]. In the United States (US), the NEMS model of the Energy Information Agency (EIA) of the US Department of Energy has been used regularly for underpinning energy policy. This model has, among others, been used to analyze the impact of the proposed American Clean Energy and Security Act of 2009, and is used to generate the annual energy outlook (AEO) of the US [40]. Other popular examples of long-term energy-system planning models used for policy support are MARKAL/TIMES [24, 25, 41] (see e.g., [42, 39, 43]), MESSAGE [26] and PERSEUS [44, 45, 46].

The focus in this dissertation is on the challenges related to using long-term energy-system planning models, and more specifically ESOMs, in the context of an increasing penetration of IRES and the liberalization and deregulation of the electricity markets. In this context, two specific challenges for ESOMs are identified.

1.2.2 Challenge 1: capture the challenges related to integrating IRES

A first challenge relates to having a sufficiently high level of temporal, technical and spatial detail to capture the challenges related to integrating large shares of IRES. Due to the fact that long-term energy-system planning models typically cover a time horizon of multiple decades, are technology rich and span a large geographical area, solving these models is computationally demanding. To maintain tractability, as a rule, these models use a low level of temporal, technical and geographical detail. More specifically, these models typically use 4 to 48 so-called time slices to represent intra-annual variations in demand and supply. Furthermore, these models operate at a technology-type level rather than considering the individual power plants and corresponding technical operational constraints (e.g., minimum operating point, minimum up and down times, etc.). For modeling past power systems, which consisted predominantly of conventional dispatchable power plants, such simplifications were shown to have a limited impact on the results [8, 47]. However, accurately reflecting the economic and technical challenges related to a large-scale penetration of IRES requires modeling the variability in system load and renewable generation, the limited flexibility of thermal units and the spatial smoothing of the variable output of IRES across multiple geographical regions. This requires models with a high level of temporal, technical and spatial detail. Unfortunately, incorporating yearly data series at an hourly resolution while also modeling technical operational constraints at a power-plant level is currently computationally not feasible for planning models [8, 48]. This level of detail is typically reserved for operational power-system models, such as unit commitment and economic dispatch models (see e.g., [49]). These models, however, do not consider the long-term evolution of the power system (i.e., the portfolio of power plants is fixed in these models). In this regard, Pfenninger et al. [47] identify resolving details in time and space as the main challenge for long-term energy-system planning models. Bridging the gap between long-term planning models and operational power-system models has recently become an active field of research.

1.2.3 Challenge 2: simulate decision making of private agents in electricity markets for descriptive scenarios

As discussed above, ESOMs are both used from a normative perspective and from a descriptive perspective. For the latter, these models aim to simulate/describe the likely evolution of the system under certain assumed boundary conditions (e.g., the policy framework, the evolution of primary fuel prices, etc.). Since (i) in liberalized and deregulated electricity markets investment decisions are made by private, profit-maximizing, companies and (ii) the investment decisions of these agents are influenced by the market design and the policies in place, these models should be able to reflect the decision making rational of private companies as well as specific market designs and policies.

However, ESOMs are typically formulated from a societal welfare perspective (minimizing total system cost) and do not explicitly represent different agents and markets. In this regard, ESOMs rely on economic theory stating that the total surplus is maximized (or the total cost is minimized) in the equilibrium found in competitive markets where different economic agents aim to maximize their own profit (relating to the famous invisible hand of Adam Smith) [25, 50, 51]. Thus, by minimizing total system cost/maximizing total surplus, the competitive equilibrium can be computed. A direct consequence is that optimization models cannot be used to compute the equilibrium whenever generation companies behave strategically (e.g., whenever they could abuse market power). However, to what extent ESOMs are capable of reflecting specific market designs, policy interventions or the decision making of private generation companies facing a lot of uncertainty is unclear.

These challenges for ESOMs are schematically summarized in Fig. 1.1.

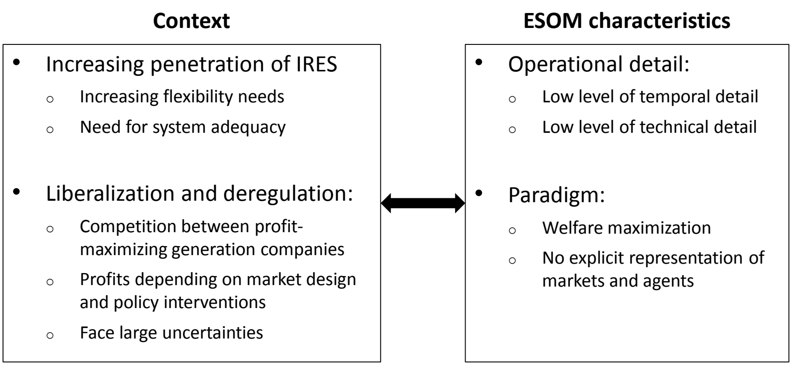


Figure 1.1: Schematic representation of the challenges faced by ESOMs in the context of the liberalization and deregulation of the electricity markets and an increasing penetration of IRES.

1.3 Scope and objectives

1.3.1 Objectives

The main research questions addressed in this PhD dissertation directly relate to the challenges for ESOMs identified above. They are listed below:

- What is the impact of using a low level of temporal and technical detail in long-term energy-system planning models when developing scenarios with a high penetration of IRES?
- How can long-term energy-system planning models be adapted to reflect the main challenges related to integrating large shares of IRES in the electric power system? More specifically:
  - how to capture the intermittent character of IRES without having to drastically increase the number of time slices?
  - how to capture the limited flexibility of conventional, dispatchable power plants without having to model individual power plants and their corresponding technical constraints and cycling costs?
- To what extent can ESOMs reflect specific market designs, policy interventions or the decision making of private generation companies in descriptive scenarios?

These central research questions are respectively tackled in Chapters 3-6, in which the main contributions of the research presented in this dissertation is situated.

1.3.2 Scope

There are different types of long-term planning models (as will be discussed in Chapter 2). The focus in this work is specifically on energy-system optimization models (ESOMs), such as MARKAL/TIMES models [24, 25] and the MESSAGE model [26]. However, the research related to the levels of temporal and technical detail in planning models directly translates to different types of energy-system planning models as well as long-term power-system planning models. Despite the fact that our interest lies with ESOMs, this dissertation focuses on the electrical power system within ESOMs.

In order to bridge the gap between energy-system planning models and operational power-system models in terms of the level of temporal, technical and spatial detail, multiple approaches can be conceived. In the recent literature, two fundamentally different groups of approaches can be identified. A first group of approaches scrutinizes the results of the energy-system planning model with dedicated operational models, with the goal of better interpreting the results (unidirectional soft-link, e.g., [52]), or improving the results of the energy-system planning model by adapting some of its parameters (bidirectional soft-link, e.g., [53, 54]). A second group of approaches aims to directly increase the level of detail in planning models, either focusing on the level of temporal detail (e.g., [55, 56, 57]) or on the level of technical detail (e.g., [8, 58]). For a more detailed discussion of both approaches, we refer to [59]. In the work presented in this dissertation, the focus is on approaches which directly increase the level of temporal and technical detail. Increasing the level of spatial detail is out of the scope of this work.

1.4 Outline

The outline of the remainder of this dissertation is as follows:

Chapter 2 presents a categorization of different types of long-term planning models.

Chapter 3 gives an overview of the level of temporal and technical detail typically employed in ESOMs and evaluates the impact of these model simplifications on the results provided by ESOMs. In addition, insights into how the low level of temporal and technical detail impacts the results are provided. This chapter is based on:

- Poncelet, K., Delarue, E., Six, D., Duerinck, J., and D'haeseleer, W. *Impact of the level of temporal and operational detail in energy-system planning models.* Applied Energy 162 (Jan. 2016), 631–643.
- Collins, S., Deane, J. P., Poncelet, K., Panos, E., Pietzcker, R. C., Delarue, E., and Ó Gallachóir, B. *Integrating short term variations of the power system into integrated energy system models: A methodological review.* Renewable and Sustainable Energy Reviews 76, Supplement C (2017), 839 – 856.

Chapter 4 focuses on the temporal representation in planning models. First, different traditional and state-of-the-art methods of time-slicing which have been used in the literature are presented. These different time-slicing methods are subsequently evaluated. Next, the chapter zooms in on one specific method of time-slicing which is based on using the data of a limited number of representative historical periods (e.g., days). Specifically, the focus is on methods to select a set of days representative for a typical year. New methods of selecting representative days are developed and compared to methods available from the literature. This chapter is based on:

- Poncelet, K., Delarue, E., Six, D., Duerinck, J., and D'haeseleer, W. *Impact of the level of temporal and operational detail in energy-system planning models.* Applied Energy 162 (Jan. 2016), 631–643.
- Collins, S., Deane, J. P., Poncelet, K., Panos, E., Pietzcker, R. C., Delarue, E., and Ó Gallachóir, B. *Integrating short term variations of the power system into integrated energy system models: A methodological review.* Renewable and Sustainable Energy Reviews 76, Supplement C (2017), 839 – 856.
- Poncelet, K., Höschle, H., Delarue, E., Virag, A., and D'haeseleer, W. *Selecting representative days for capturing the implications of integrating intermittent renewables in generation expansion planning problems.* IEEE Transactions on Power Systems 32, 3 (May 2017), 1936–1948.

Chapter 5 focuses on the level of technical detail in planning models. First, a review of the level of technical detail used in state-of-the-art ESOMs and power-system optimization models (power-system optimization models (PSOMs)) is provided. Next, the relevance of including technical constraints in ESOMs is analyzed in depth. In this regard, the impact of the share of IRES, the capacity mix, the assumed flexibility of dispatchable thermal power plants, and the availability of other sources of flexibility on the impact of incorporating technical constraints is considered. Next, the focus shifts towards the development of reduced, less computationally demanding formulations to approximate the impact of including detailed technical constraints. An investment planning model with integrated clustered unit commitment constraints is developed and serves as a reference for evaluating the reduced formulations. To develop these reduced formulations, first the impact of specific technical constraints is analyzed. The resulting insights are then used to develop the simplified formulations, which are finally evaluated in terms of accuracy and speed-up. This chapter integrates elements of:

- Meus, J., Poncelet, K., and Delarue, E. *Applicability of a clustered unit commitment model in power system modeling.* IEEE Transactions on Power Systems, 99 (2017).

Chapter 6 focuses on the limitations of optimization models for representing specific market designs, policy interventions and behavioral characteristics of agents. First, an overview of the limitations of optimization models is derived by analyzing how an equilibrium problem and an optimization problem can be cast into a mixed complementarity problem (MCP). These limitations are subsequently illustrated by presenting three examples of equilibrium problems which are relevant for long-term planning in deregulated electricity markets but cannot be solved directly using optimization models.

Chapter 7 finally summarizes the main findings of the work presented in this dissertation and provides indications for future research.

Chapter 2

Long-term energy-system planning models

To analyze possible transition pathways, a myriad of long-term planning models has been developed. The aim of this chapter is to categorize different types of planning models[1]. Two criteria for categorizing planning models are used in this chapter. A first criterion relates to the *scope* of the model, i.e., the sectoral, geographical and temporal coverage of the model. A second criterion relates to the *methodology* used to generate transition pathways. The scope and the methodology of the planning model determine the type of research questions that can be addressed using the planning model and are hence relevant criteria for choosing the type of planning model to use or develop. In addition, both the scope and the methodology have an impact on the level of temporal and technical detail that can be tractably incorporated as well as the degree with which agents, markets and policy interventions can be represented. As such, the presented categorization is also relevant in the context of the objectives set out for this dissertation.

The remainder of this chapter is as follows. Sections 2.1 and 2.2 present the categorization of long-term planning models based on the model scope and the employed methodology, respectively. Next, Section 2.3 relates the model scope to the different methodologies by giving an overview of which methodologies are commonly used depending on the scope of the model. Finally, the conclusions are presented in Section 2.4.

[1] It must be noted that the goal is not to provide an overview of specific modeling tools and their characteristics. For a review of specific modeling tools, we refer to [46, 60].

2.1 Categorization based on the model scope

The *scope* or coverage of different types of planning models determines the interactions which are endogenously accounted for in the model, and hence, the type of questions that can be addressed using the model. Moreover, the scope is directly linked to the level of detail that can be incorporated, which also impacts the questions which can be dealt with by the model. The incorporated level of detail can be restricted by the computational complexity of executing the model, but other aspects such as data requirements, and transparency play a role as well [61].

Based on the scope of the model, we distinguish between the following types of long-term planning models[2]:

- Integrated assessment models,
- Energy-economy models,
- Energy-system planning models,
- Power-system planning models.

These different type of models are discussed below. In this section, we refrain from making statements regarding the methodologies typically used for these types of models. The different methodologies are first discussed in Section 2.2. The link between the model scope and commonly deployed methodologies is presented in Section 2.3.

2.1.1 Integrated assessment models

Integrated assessment models (IAMs) are characterized by their scope and aim. In contrast to the energy-system planning models which mainly focus on near-term energy system transformations in a certain region or in an individual country, IAMs are used to analyze long-term interdisciplinary questions of a global scope. Recently, IAMs have been applied frequently for assessing policies to mitigate climate change (see e.g., [62, 63]). To do so, IAMs generally not only consider the global energy system, but also incorporate for instance macro-economic interactions, demographics and resource availability restrictions (e.g., materials, water, land) and/or non-energy greenhouse gas (GHG) emissions. The time horizon of IAMs typically spans 50-150 years, i.e.,

[2] It must be noted that the boundaries between these different types of models are ambiguous.

the time scales required for analyzing climate change mitigation [57]. Typical research questions addressed by IAMs include analyzing the cost of climate stabilization, determining the boundary conditions for climate stabilization feasibility and analyzing the distribution of mitigation and adaptation efforts [64]. Well-known examples of IAMs are MESSAGE [26], IMAGE [65], GCAM [66] and POLES [67, 68].

2.1.2 Energy-economy models

Energy-economy models address the interaction between the energy system and the overall economic system. The sectoral scope of these models is thus also not solely restricted to the energy system. The geographical scope of energy-economy models varies from a single country or region up to global models, while the time horizon considered is generally 20-100 years. The main motivation for using energy-economy models is that these models allow accounting for the economy-level response (e.g., changes in sectoral composition, trade, employment and welfare) to changes in the energy-system (for instance resulting from policy interventions and/or technological evolution) and vice versa [69]. Examples of energy-economy models are NEMS [40], the US-REGEN model [69], the MESSAGE-MACRO model [70] and the TIMES-MACRO model [71].

2.1.3 Energy-system planning models

Energy-system planning models restrict the scope to the evolution of the entire energy system in a particular region or country over a time horizon spanning multiple decades. Typically, energy-system planning models cover the entire chain from extraction and refining of primary fuels to conversion and final consumption. In contrast to the energy-economy models discussed above, the interactions between the energy sectors and other economic sectors is not endogenously accounted for. The advantage of the more restricted scope is that a more detailed description of the energy system can be provided. The main strength of these energy-system planning models is that they provide a comprehensive description of possible scenarios for the transition of the energy system by considering the inter-sectoral, inter-temporal and inter-regional relationships. First, as these models typically cover all energy sectors (e.g., electrical power, heating, transportation) with a high level of technological detail, these models allow analyzing the complex interactions between different energy sectors and technologies. That is, different energy technologies used in different energy sectors can compete to acquire the same resources. These resources can be primary fuels (e.g., the heating and electricity sector are in direct competition for acquiring natural gas), energy carriers (e.g., the heating and transportation sector compete for electricity which can facilitate decarbonization of both sectors via increased electrification), or emission budgets/allowances (e.g., in the European Union (EU) emission trading scheme (ETS), the power sector competes with other energy-intensive industries for attaining emission allowances). Second, energy-system planning models allow analyzing the impact of inter-temporal relationships, such as technology lock-in effects or the costs related to delayed climate mitigation. Finally, the impact of inter-regional trade and policies can be analyzed. For these reasons, these models provide valuable information to decision makers for, among others, (i) setting policy targets (e.g., distributing an overall GHG emission reduction target across the EU ETS and the non-ETS sectors [72], distributing the targets for the different non-ETS energy sectors, the evolution of these targets over time), (ii) assessing the feasibility and the boundary conditions for the feasibility of achieving certain policy targets (e.g., assessing the costs associated to the policy targets or the impact of consumer acceptance of nuclear energy and carbon capture and storage technologies on the feasibility of achieving certain emission reduction targets), (iii) assessing the policies required to achieve these targets (e.g., taxes, subsidies) and (iv) developing R&D policy (see e.g., [37]). In this regard, well-known energy system planning models such as PRIMES [38] and MARKAL/TIMES [24, 25] have been frequently applied for shaping European energy policy [42].

2.1.4 Power-system planning models

Power-system planning models restrict the scope to the electrical power sector (including investments in generation capacity and/or transmission capacity). The interactions between other energy sectors such as the heating sector and the transportation sector are thus not endogenously accounted for. Therefore, the impact of other energy sectors on the power sector needs to be considered via exogenously determined parameters. Examples of such parameters are the electricity generation of CHP units and the electricity consumption of the heating sector. The advantage of a more restricted scope is again that it allows increasing the level of detail (temporal, technical and spatial) compared to the more broad energy-system planning models [52]. Given the important role the power sector is expected to play in decarbonizing the energy system, power-system planning models have been used extensively to analyze the evolution of the power system. In this regard, these models have been used to determine the cost-optimal capacity mix to achieve certain policy targets (e.g., [73, 74]), to determine the costs associated with achieving certain policy targets for the electrical power sector (e.g., [75]), to analyze the value and need for different flexibility options (e.g., [76, 77, 78, 79, 73]), as well as to provide projections of future wholesale electricity and emission allowance prices (e.g., [35, 80, 81, 82]) and their impact on the profitability of certain assets (e.g., [83, 73]), amongst others. Well-known examples of power-system planning models are ReEDs [84], LIMES [85], Switch [86] and the Resource Planning Model [87].

2.1.5 Summary

A summarizing overview of the scope of the different types of long-term planning models is provided in Tab. 2.1.

2.1.6 Positioning with respect to operational power-system models

In this work, the focus is on energy-system and electrical power-system planning models. More specifically, the main focus is on the representation of operational aspects of the electrical power system in long-term energy-system and electrical power-system planning models. Therefore, we briefly position long-term planning models with respect to more detailed operational models of the electrical power system.

The main distinction between long-term planning models and operational electrical power-system models is the fact that no investments are considered in operational electrical power-system models, i.e., the capacity mix and network infrastructure are input data for operational power-system models. In contrast, investments in additional generation technologies and transmission lines form one of the main outputs of overall energy-system and electrical power-system planning models.

Given the complexity of the electricity system and the different challenges involved in operating that system, a variety of operational power-system models have been developed. The applications of this set of models include, among others, power flow analysis, scheduling the on/off state and power generation of individual generating units and maintenance scheduling. The different models used for these purposes operate on time frames ranging from milliseconds to an entire year. The models used on very short time frames are typically engineering models which are valuable for system operators to ensure reliability. As the timeframe of the model increases, the engineering detail is typically reduced and more economic aspects are introduced. An overview of these different models is presented in Fig. 2.1.

	Integrated assessment models	Energy-economy models	Energy-system planning models	Power-system planning models
Sectoral scope	Energy system + economy* + demography* + resource availability* + non-energy GHG emissions*	Entire economy	Energy system	Power system
Time horizon	50-150 years	20-100 years	20+ years	1-50 years
Geographical scope	Global	Single country - global	Single country - multiple countries	Single country - multiple countries
Well-known examples	MESSAGE [26], IMAGE [65], GCAM [66], POLES [67]	US-REGEN [69], MESSAGE-MACRO [70], NEMS [40], TIMES-MACRO [71]	MARKAL [24], TIMES [25], PRIMES [38]	ReEDS [84], LIMES [85], RPM [87]

Table 2.1: Overview of the scope of different types of long-term planning models. The sectoral, temporal and geographical scope of the different types of planning models presented in this table are not absolute, but serve to indicate the typical ranges. A * indicates an aspect which might be covered but is not necessarily covered.

In this dissertation, we aim to improve long-term planning models by integrating higher levels of temporal and technical detail, which are currently typically reserved for operational models such as unit commitment (UC) and economic dispatch (ED) models. UC models are techno-economic models which aim to schedule the on/off status (i.e., the commitment decisions) and the actual level of power generation of individual generation units (i.e., the dispatch decisions) in order to minimize the operational system costs. Due to the fact that most traditional electrical power generation units cannot start-up very quickly, the

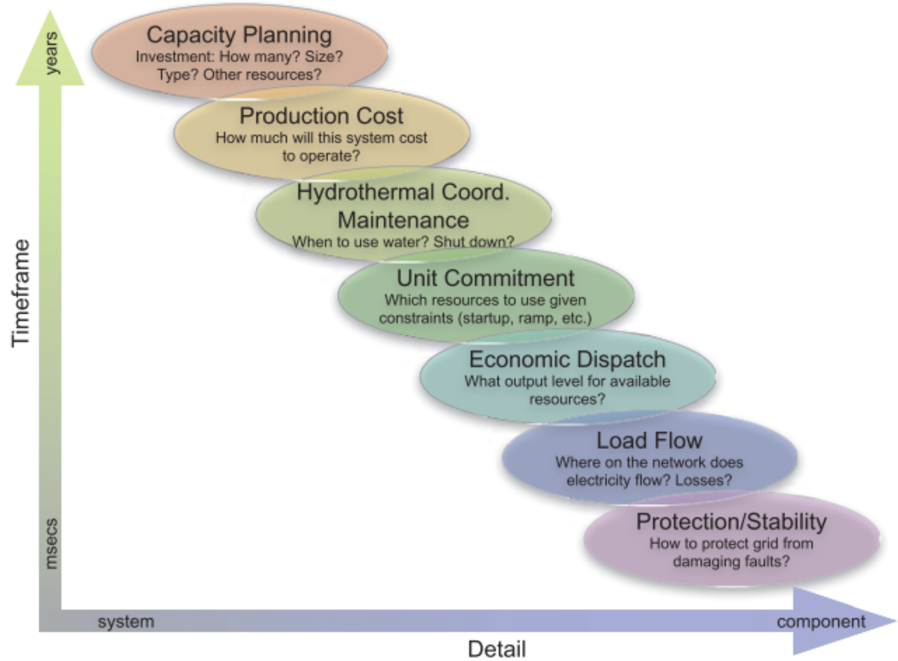


Figure 2.1: Overview of different power-system models. Picture taken from [88].

on/off status (i.e., the commitment status) should be known a number of hours to days before the actual power delivery. Hence, the time horizon used in UC models typically spans a day to a week. This time horizon is disaggregated in different time steps with a resolution in the range of 5 minutes up to one hour. Once the commitment schedule of all plants is determined, ED models can be used to determine the power output of all online units (i.e., the dispatch decisions) in order to minimize the operational costs. These dispatch decisions can differ from those planned in the UC model since better forecasts are available closer to real time. The solution provided by UC and ED models should respect technical constraints on the system level and on the generation unit level. On the system level, these constraints include, e.g., transmission constraints and reserve requirements. On the unit level, each generation unit faces a number of technical constraints such as a minimal operating level, restricted ramping rates and minimum up and down times. In addition, to determine the optimal solution, also start-up costs and efficiency losses during part-load operation need to be considered. To account for these technical aspects in UC models, the on/off status of each individual unit in every time step needs to be considered, which can be represented via binary variables. As such, most UC models currently rely on mixed integer linear programming (MILP). Due to the large number of binary variables, solving UC models for large electrical power systems can be computationally challenging. Examples of UC models include PLEXOS [89] , LUSYM [49], and GTMax [90].

2.2 Categorization based on the methodology

A second way to categorize long-term planning models is based on the deployed *methodology*. In this regard, a variety of methodologies is being used. Here, we mention the following methodologies:

- Computable general equilibrum models
- Optimization models
- Equilibrium models
- System-dynamics models
- Agent-based models

A brief overview of these different methodologies is presented below. It must be noted that this list of methodologies is not exhaustive and that there is not always a clear boundary line between different methodologies. Certain models, such as for instance the PRIMES model and the NEMS model are difficult to categorize within one of the above presented methodologies, but they use elements of computable general equilibrum models, optimization models and equilibrium models.

To categorize the different methodologies, different criteria will be considered. A first main criterion is the distinction between bottom-up and top-down models. Whereas top-down models represent the entire economy or specific economic sectors in an aggregated way via production functions, bottom-up models are typically technology-explicit and technology rich, meaning that the energy system is described by modeling specific technologies or units and their interactions.

A second key criterion relates to whether the methodology takes a normative/prescriptive perspective, or whether a descriptive perspective is taken. The perspective taken directly relates to the objective of the modeling methodology. If the perspective is normative, the objective of the methodology is to determine what is optimal from a societal perspective. In contrast, if the perspective is descriptive, the objective of the methodology is rather to simulate the outcome of the market(s). Since the perspective taken is directly related to the objective of the modeling methodology, it also has a direct relation to the modeling methodologies which can be used. Tab. 2.2 provides an overview of this relationship between the perspective taken, the objective of the model and the modeling methodologies which can be/are being used.

Perspective	Modeling objective	Modeling methodology
Normative/prescriptive	Determine what is best for society (maximize welfare)	CGE models, optimization models
Descriptive	Simulate the expected market(s) outcome	CGE models, optimization models, equilibrium models, system-dynamics models, agent-based models

Table 2.2: Relationship between the perspective taken, the objective of the model and the modeling methodologies which are/can be used.

As can be seen from Tab. 2.2, all methodologies discussed here can be used from a descriptive perspective, whereas only CGE and optimization models are regularly used from a normative perspective[3]. To distinguish between the different modeling methodologies capable of taking a descriptive perspective (i.e., simulating the outcome of the markets), different criteria will be considered for the methodologies described below. These criteria include how different agents and market distortions are/can be represented and the type of equilibrium which is computed.

2.2.1 Computable general equilibrium models

Computable general equilibrum (CGE) models represent the entire economy of a certain region (e.g., a country) via a description of the different economic sectors. Each economic sector is represented by a production function, i.e., the output of a specific sector is related to the main factors of production such as capital, labor and energy. The mix of inputs required to achieve one

[3]It must be noted that equilibrium models can in principle determine what is best for society by computing the equilibrium in perfect markets. However, the strength of equilibrium models lies in the ability to simulate imperfect markets. These models are therefore rarely used to simulate perfect markets.

unit of output in every sector can vary via elasticities of substitution. These production functions are typically calibrated based on historical market data. The economic equilibrium is then found by maximizing the total utility, which is a function of the consumption in the different sectors [91]. Due to the fact that the production functions are typically calibrated to historical market data, most CGE models indirectly capture the behavior of agents and market distortions and implicitly take a more descriptive perspective [27]. CGE models are furthermore classified as general-equilibrium and top-down models. The term general equilibrium refers to the fact that the equilibrium spans all economic sectors and their interactions. As stated earlier, the label top-down refers to the fact that the entire economy or the different economic sectors are represented via aggregated production functions rather than composing the system as a set of interlinked technologies [27, 92]. As such, CGE models typically have difficulties in representing the interplay between individual technologies and technical operational constraints [27].

CGE models can either be used directly or can be soft-linked to bottom-up models of the energy system. In the first case, i.e., the direct use, the energy sector can be represented explicitly and can be further disaggregated into different subsectors (e.g., the electrical power sector, the transportation sector, etc.), each having their own production function. The economic activity in the different economic sectors then results in a demand for the output of each of these energy subsectors, i.e., final energy such as energy for transportation and electricity. For these energy subsectors, the calibration of the production functions can be based on more detailed bottom-up models (see e.g., [93]) or through empirical data [64]. In the second case mentionned above, a less detailed CGE model is soft-linked to an energy-system model (see e.g., [71, 94]), resulting in a hybrid bottom-up and top-down model. In this case, the energy-system model typically determines the energy-system costs which is used as input in the CGE model. The CGE model then provides the equilibrium given these energy-system costs. One of the outputs of the CGE model is the energy demand which is used as input to the energy system model. Both models can then be solved iteratively until convergence is achieved.

2.2.2 Optimization models

Optimization models are bottom-up models of (a part of) the energy system in a certain region. Bottom-up models are technology explicit, i.e., these models describe the overall energy & electricity system as an interlinkage of different explicitly defined technologies, as visualized in Fig. 2.2. For this reason, bottom-up models are also referred to as 'technology-rich' or 'engineering' models. Optimization models simultaneously determine the investments in different energy technologies and the operational decisions which maximize the total economic producer and consumer surplus[4]. Frequently, the demand for energy services is assumed to be inelastic. In that case, maximizing total surplus boils down to minimizing the total system costs. The surplus maximization/cost minimization problem is restricted by a number of constraints. These constraints specify technical and policy restrictions which need to be considered. Optimization models can first of all be used from a normative perspective to provide information on how certain objectives can be cost-effectively realized. Second, optimization models can be used to determine the equilibrium in the energy markets and hence can also take a descriptive perspective. For this descriptive perspective, optimization models rely on the fact that total surplus is maximized in the equilibrium found in competitive markets. As will be discussed in detail in Chapter 6, optimization models are limited in their ability to represent deviations from perfect competition. Therefore, optimization models are sometimes called 'optimistic' in contrast to the 'pessimistic', change-resistant, CGE models [27, 95]. Another difference with CGE models is that the scope of optimization models is restricted to (a part of) the energy system, being in turn merely a part of the overall economic system. As such, the equilibrium obtained using such a model is referred to as a partial-equilibrium. Optimization models are correspondingly referred belong to the group of partial-equilibrium models.

2.2.3 Equilibrium models

Equilibrium models, similar to optimization models, can be classified as bottom-up partial-equilibrium models and thus differ fundamentally from CGE models (as discussed in the section above). However, in contrast to optimization problems which take a system perspective, equilibrium models explicitly consider different agents. Each agent has his own objectives, decision variables and constraints which are expressed in an optimization problem (e.g., profit maximization problem). These different agents participate in markets, which are typically represented by so-called linking constraints. These constraints typically state that the total production and consumption of a commodity must be in balance or that the total production of a certain commodity is capped. Equilibrium models then aim to find the equilibrium between the different agents operating in the different markets. By explicitly considering the objectives and incentives of different agents, equilibrium models can analyze

[4]In this dissertation, we frequently refer to the objective function of optimization models as maximizing the total surplus, being the sum of the producer and the consumer surplus. It should be noted that it would be more general and correct to refer to the objective function of optimization models as maximizing the difference between the utility (i.e., the value related to consumption) and the production costs.

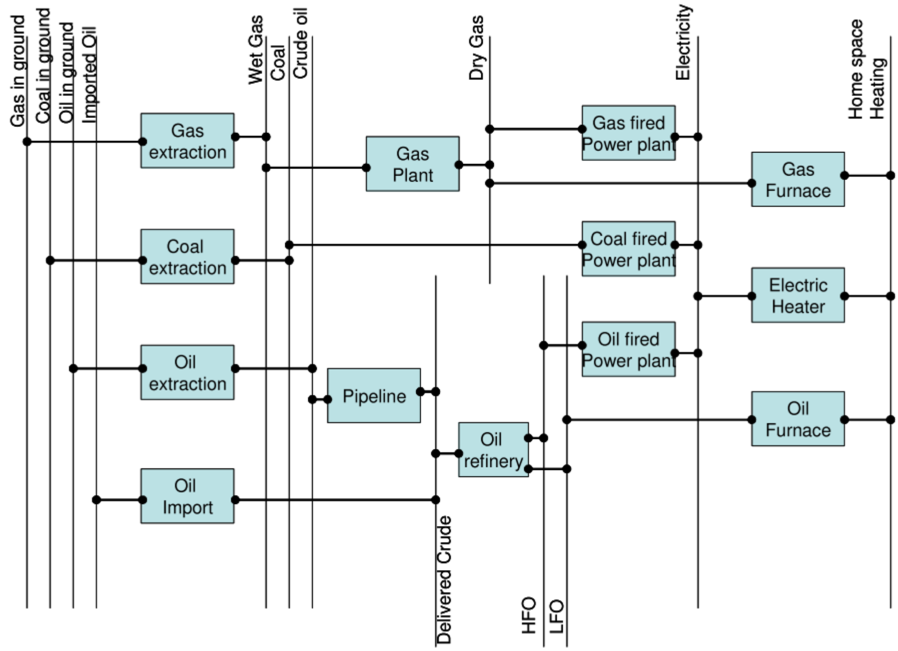


Figure 2.2: Illustration of the bottom-up representation of an overall energy system in optimization models. Picture taken from [25].

the impact of market imperfections on the equilibrium. In this regard, many equilibrium models have been developed to analyze the impact of strategic behavior in imperfectly competitive markets. Depending on the assumptions made regarding the behavior of the agents, different types of equilibria can be distinguished, e.g., Nash equilibria, Nash-Cournot equilibria, Stackelberg equilibria, etc [96]. Aside from strategic behavior, equilibrium models also provide more flexibility to analyze the impact of other market distortions which cannot be analyzed easily using optimization models[5]. As such, equilibrium models are typically used from a descriptive perspective. Depending on the problem at hand, different mathematical formulations are used to formulate the equilibrium problem. These include mixed complementarity problems (MCPs), a mathematical problems with equilibrium constraints (MPECs) and equilibrium problems with equilibrium constraints (EPECs). Each of these types of problem formulations has its own dedicated solution strategies. However, in

[5]The limitations of representing different market imperfections in deregulated electricity markets whenever price-taking agents are assumed will be discussed in detail in Chapter 6.

general, solving equilibrium models is significantly more difficult than solving optimization problems. As a result, the scope and detail of equilibrium problems is typically significantly smaller than the scope and detail used in optimization models. For instance, the literature contains few long-term investment planning equilibrium problems which span multiple years.

2.2.4 System-dynamics models

System-dynamics models represent the dynamics of the evolution of an energy system by explicitly describing the causal relationships between different decisions and the signals provided by the markets. These relationships are typically visualized in so-called causal loop diagrams which make apparent the positive and negative feedback loops as well as the delays in the response of the system [15]. An example of such a causal loop diagram for investments in the electrical power sector is presented in Fig. 2.3. From a mathematical perspective, the expressions of these relationships typically form a set of non-linear differential equations [97, 15, 98, 99]. Dedicated numerical methods are then used to solve this set of equations [15]. Thus, in contrast to the equilibrium problems discussed in the previous section, which describe the decision making of different agents indirectly through a set of linked optimization problems, system-dynamics models explicitly define the relationships between a decision variable (e.g., an investment decision) and certain signals provided by the market (e.g., electricity prices). This provides more flexibility to model the dynamic response of the system (e.g., the delayed response of investment decisions to increasing electricity prices). As such, system-dynamics models can deviate, for instance, from the assumption of perfectly rational, forward-looking agents. However, a disadvantage of these models is that assumptions need to be made regarding the relationships describing the decision making [97]. In contrast, optimization models and equilibrium models can rely on economic equilibrium theory. System-dynamics models have recently been applied frequently for analyzing the need for capacity remuneration mechanisms for ensuring generation adequacy in the electrical power sector (see e.g., [15, 19, 99, 100]).

2.2.5 Agent-based models

Similar to equilibrium models, agent-based models determine the evolution of the energy system as a result of the decisions made by multiple explicitly defined agents. However, in contrast to equilibrium models, the different agents are represented by behavioral algorithms. These algorithms typically contain both conditional logic and learning algorithms [101, 102]. This learning relates

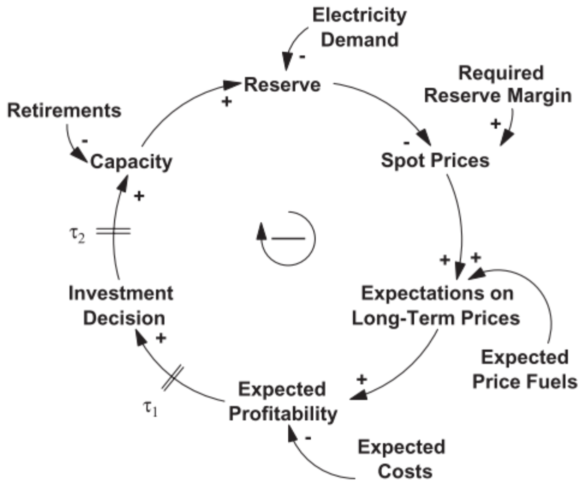


Figure 2.3: Illustration of the causal loop diagram of a system-dynamics model for the electrical power sector. Picture taken from [15].

mainly to the bidding in the short-term electricity markets where a high number of repeated games allows the agents to learn by experimenting with different bidding strategies. This way, in the model philosophy, agents can, for instance, notice that they have market power and start exhibiting strategic behavior without needing to specify up front that this particular agent will behave strategically. In this regard, agent-based models have been applied frequently to analyze market power and price formation in wholesale electricity markets (see e.g., [101, 103, 104]). In addition, a number of applications of agent-based models also exist for long-term investment planning (see e.g., [101, 102, 105]). However, for investment-decision making, learning is more difficult as there are no repeated games and the feedback on whether a certain investment decision has been a good one comes with a long delay. Therefore, the investment decisions in agent-based models are typically rule-based. An example of the investment-decision making algorithm used in the EMLab-Generation model is presented in Fig. 2.4. In agent-based models, the evolution of the energy system directly follows from the decisions made by the different agents which are based on predefined algorithms. As a result, the outcome of the different agents thus not necessarily reflects an economic equilibrium situation. Another big difference with the above-described methodologies is that agent-based models are not solved at once but consist of a number of modules/algorithms which are executed sequentially (as can also be observed in Fig. 2.4). This provides a lot of flexibility for integrating more detailed elements (e.g., market distortions, specific market clearing algorithms, feedback, perceptions and inertia) [15, 106].

The drawback however is that a lot of assumptions need to be made which can be difficult to underpin [97, 107], thereby reducing the transparency of the results [92].

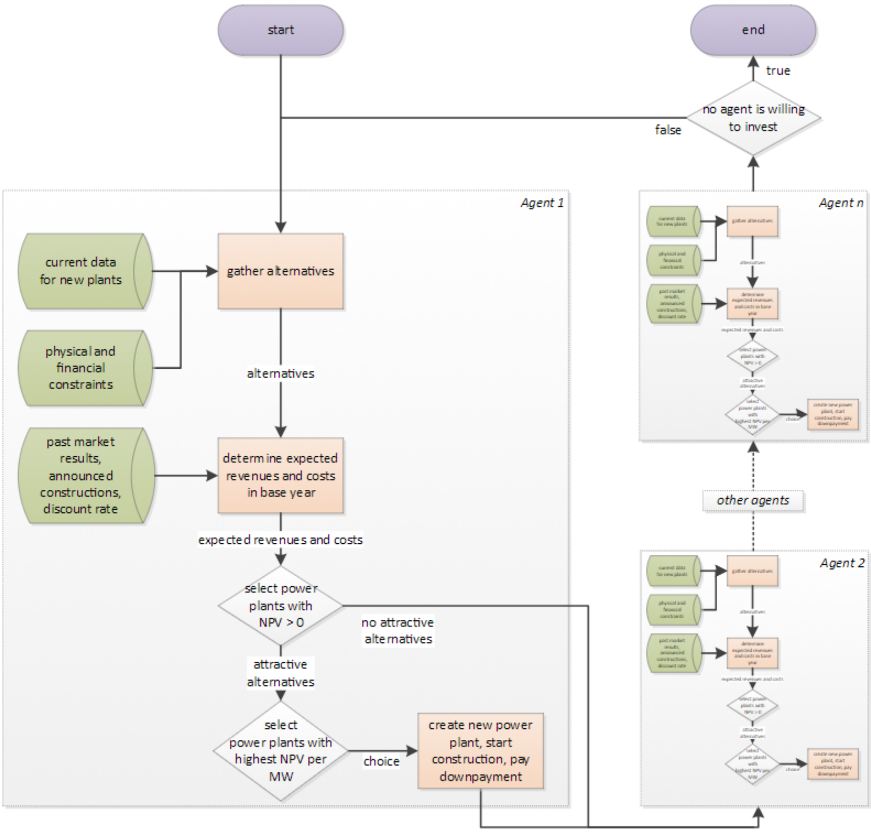


Figure 2.4: Illustration of an investment algorithm in the EMLab-Generation agent-based model. Picture taken from [15].

2.2.6 Summary

A schematic overview of the main characteristics of the different methodologies is provided in Tab. 2.1. As discussed, all methodologies can be interpreted from a descriptive perspective. However, these methodologies differ in their philosophy and the level of detail used in describing the energy system, the agents and the different markets.

	CGE models	Optimization models	Equilibrium models	System-dynamics models	Agent-based models
Technological detail	Top-down or hybrid	Bottom-up	Bottom-up	Bottom-up	Bottom-up
Perspective	Normative or descriptive	Normative or descriptive	Descriptive	Descriptive	Descriptive
Equilibrium	Yes, general equilibrium	Yes, partial equilibrium	Yes, partial equilibrium	No (proven) equilibrium	No (proven) equilibrium
Agent representation	No explicit agents, behavior indirectly considered via calibration production functions	No explicit agents, price-taking agents implicitly assumed	Explicit agents, each agent represented by its own optimization problem	No explicit agents, behavior indirectly specified via mathematical functions	Explicit agents, agents are represented by behavioral algorithms
Market distortions	Indirectly considered via calibration production functions	Limited possibility in representing market distortions	Yes	Yes	Yes
Well-known examples	EPPA [91], MESSAGE-MACRO [70]	TIMES [25], ReEDS [84]	Höschle et al. [108], Wogrin et al. [109]	Ochoa and van Ackere [99], Olsina et al. [15]	EMLab Generation [102], PowerACE [97]

Table 2.3: Overview of the main characteristics of the methodologies deployed for long-term planning.

2.3 Relationship between the model scope and the methodology employed

Depending on the scope of the model, different methodologies are typically deployed. An overview of the relationship between the model scope and the methodologies generally used is presented in Fig. 2.5.

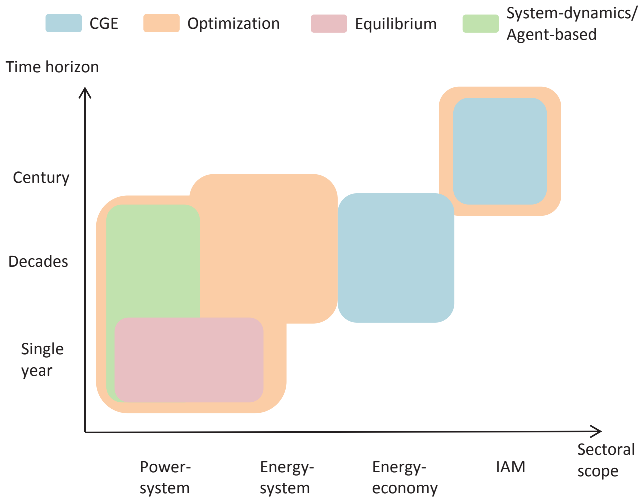


Figure 2.5: Relationship between the scope and the methodologies used in planning models. CGE stands for computable general equilibrum, IAM stands for integrated assessment model.

This figure shows that optimization models have the broadest domain of application, as they are commonly used for electrical power-system planning models, overall energy-system planning models, as well as integrated assessment models (IAMs). In contrast, system-dynamics models and agent-based models have been applied mainly for electrical power-system planning purposes. Similarly, equilibrium models have mainly been applied for analyzing investments in the electricity markets, but have also been applied to analyze investments in other markets such as the natural gas markets (see e.g., [110]). However, due to the high computational cost, equilibrium models are currently mainly employed for analyzing small scale or highly simplified systems. Finally, CGE models have a unique position as these are the only commonly used models which can account for the interaction between the overall energy system and the broader economic system.

2.4 Summary and conclusions

A myriad of different long-term planning models have been developed. In this chapter, a categorization of the main types of planning models has been presented. Two criteria are used for categorizing long-term planning models: the scope of the model and the methodology employed. Based on the scope, four types of planning models are considered: integrated assessment models (IAMs), energy-economy models, energy-system planning models and electrical power-system planning models. Based on the methodology, a distinction has been made between computable general equilibrum (CGE) models, optimization models, equilibrium models, system-dynamics models and agent-based models. Finally, the relationship between the scope of the model and the methodologies typically used has been analyzed. Of all considered methodologies, optimization models have the broadest field of application, as they are used for both electrical power-system planning models, overall energy-system planning models and IAMs. The remainder of this dissertation first of al focuses on improving long-term energy-system optimization models (ESOMs) by increasing the level of temporal and technical detail used to model the operation of the power system. A second objective is to analyze the limitations of such optimization models in terms of representing specific market design, policies and behavioral characteristics in the context of liberalized electricity markets.

Chapter 3

Impact of the level of temporal and technical detail in long-term planning models

This chapter focuses on the impact of the low level of temporal and technical detail typically used in energy-system optimization models (ESOMs). This chapter comprises three main objectives. A first objective is to assess the order of magnitude of the impact of using a low level of temporal and technical detail, and to reflect on the corresponding implications for the use of ESOMs. A second goal is to identify which of the two, the low level of temporal detail or the low level of technical detail, has the highest impact on the results. This knowledge allows to present guidelines regarding which of the two aspects should be improved with the highest priority. As the outcome of these previous analyses will point towards the temporal detail as being the most important, the final goal of this chapter is to provide insights in how the representation of temporal aspects in planning models impact results. These insights will form the basis for improved ways of representing temporal aspects in planning models. To achieve these three goals, the impact of both the low level of temporal and technical detail is quantified for a varying penetration of intermittent renewable energy sources (IRES). To this end, the results of a TIMES model inspired by the Belgian electricity system are reevaluated using models with a high level of temporal and technical detail.

The remainder of this chapter is organized as follows. First, Section 3.1 gives an overview of the temporal and technical detail typically used in ESOMs.

Subsequent, a review of the literature regarding the impact of the level of temporal and technical detail used in planning models is presented in Section 3.2. Next, Section 3.3 presents the methodology, the assumptions and the data used for quantifying the impact of the temporal and technical representation. The results of this analysis are discussed in Section 3.4. Finally, the main conclusions are formulated in Section 3.5.

This chapter is based on:

- Poncelet, K., Delarue, E., Six, D., Duerinck, J., and D'haeseleer, W. *Impact of the level of temporal and operational detail in energy-system planning models.* Applied Energy 162 (Jan. 2016), 631–643.
- Collins, S., Deane, J. P., Poncelet, K., Panos, E., Pietzcker, R. C., Delarue, E., and Ó Gallachóir, B. *Integrating short term variations of the power system into integrated energy system models: A methodological review.* Renewable and Sustainable Energy Reviews 76, Supplement C (2017), 839 – 856.

3.1 Introduction: temporal and technical representation in energy-system planning models

This section describes the main model simplifications which are made in ESOMs in terms of the level of temporal and technical detail used to describe the electrical energy system. These simplifications are in contrast with the high resolution modeling of operational electrical power-system models that have a narrower scope.

3.1.1 Temporal representation in ESOMs

Fig. 3.1 gives a schematic overview of how the temporal dimension is modeled in TIMES models. The planning horizon is divided into a set of periods, each represented by a single year (a so-called "milestone year"). In turn, these milestone years can be divided into a set of time slices, serving to represent intra-annual variations in demand and supply. In the displayed example, a year is disaggregated into four seasons, which are in turn disaggregated into weekdays (WD) and weekend (WE) periods. Finally, diurnal variations are introduced via a day (D) and a night (N) time slice, resulting in a total of 16 time slices. The duration of each time slice, i.e., the fraction of the year it represents, can differ for different time slices. Within each time slice, all parameters are fixed, i.e., the load and the availability (i.e., the capacity factor within the period corresponding to the time slice) of IRES are assigned a single value. The value assigned to the load or the availability of IRES in every time slice is typically taken as the average value of all data points of the respective time series corresponding to that time slice (e.g., the average demand for electricity in weekend nights during winter is assigned to the time slice corresponding to night periods in the weekends in the winter season)[1].

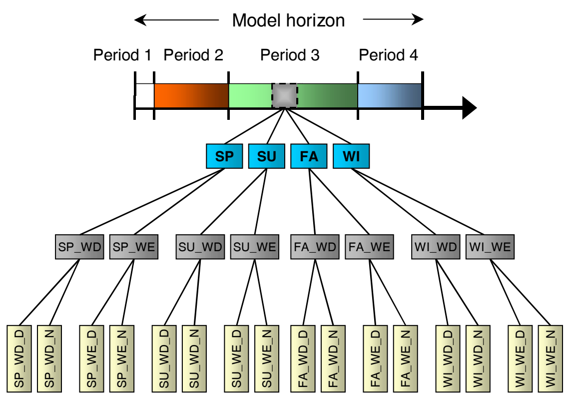


Figure 3.1: Illustration of the temporal representation in TIMES models. SP, SU, FA, WI refer to the four seasons. WE and WD refer to weekend periods and weekdays. D and N refer to daytime and nighttime periods. Picture taken from [25].

In early ESOMs, such as the MARKAL family of models, the definition of the time slices was rigid. For instance, in MARKAL, three seasonal time slices and two diurnal time slices were used. In most new ESOMs, including the TIMES model, the number of time slices used and how they are defined can be determined freely by the user. However, due to computational restrictions, the number of time slices used in large-scale ESOMs is generally restricted to 4 up to 48. The ranges presented here merely serve to indicate common practice. A frequently occurring time-slice division uses 12 time slices to distinguish between day, night and peak hours for four seasons. Examples of models using this time-slice division are the Irish TIMES model [32] and the JRC-EU-TIMES model [111]. Recently, multiple authors have investigated the impact of the stylized temporal representation and have experimented with increasing the temporal resolution and different methods to setting up the time-slice tree.

[1] It is assumed that time series of load, and IRES availability are available with a high resolution (e.g., hourly or quarter-hourly data).

Recent applications using a higher number of time slices are e.g., [30, 57]. A detailed discussion regarding these different methods for time-slicing can be found in Chapter 4.

3.1.2 Technical representation in ESOMs

In contrast to unit commitment (UC) models which consider individual power plants, ESOMs operate on a technology-type level. Hence, the load-following constraints of individual power plants and the associated cycling costs are generally not explicitly accounted for. From a technical perspective, each generation technology is typically described by an efficiency, an availability factor and an endogenously determined capacity. In terms of operational costs, fuel costs, variable operations and maintenance (VOM) costs, and taxes are accounted for. Two constraints are essential for the operation of the power system in ESOMs. A first constraint limits the instantaneous power generation of a technology-type g that has been invested in in year v (the so-called "vintage year") in every time slice t of a year y to the available capacity of that technology-type, i.e.,

$$gen_{g,v,y,t} \leq CPT_{g,v,y} AF_{g,y,t} cap_{g,v} \quad \forall g, v, y, t. \tag{3.1}$$

Here, the available capacity is limited to a fraction of the total installed capacity ($cap_{g,v}$) to account for retirements and lead times (represented by an endogenous capacity transfer parameter $CPT_{g,v,y}$). Moreover, to account for periodic maintenance and forced outages within each year, this available capacity is reduced by the availability factor $AF_{g,y,t}$. For conventional power plants, this availability factor is typically taken identical in every time slice. For IRES, the availability factor accounts for both maintenance and the limited availability of the resource (e.g., wind) within each time slice. The instantaneous power generation is unambiguously linked to a specific consumption of primary resources and corresponding greenhouse gas (GHG) emissions. A second constraint enforces a balance between the generation and demand of electricity in every time step:

$$\sum_{g,v} gen_{g,v,y,t} = DEM_{y,t} \quad \forall y, t. \tag{3.2}$$

Here $DEM_{y,t}$ is the demand for electrical power in time slice t of year y. From these constraints, it is clear that the dispatch of power plants in basic TIMES models follows the merit order (MO) in each time slice, where the instantaneous generation is only restricted by the available capacity, and not by detailed technical constraints. In addition, balancing requirements and the corresponding need for operating reserves are generally not considered.

Regularly, additional, stylized restrictions are enforced which aim to mimic the impact of detailed technical constraints. A myriad of such constraints exist. One popular example is the use of must-run requirements (see e.g., [86, 112, 113, 45, 85, 84, 87, 114, 24]). Such must-run requirements restrict changes in power output (or online capacity) between a number of time slices belonging to a parent time slice and are frequently used to limit the flexibility of baseload technologies such as nuclear and coal-fired power plants. For instance, it is sometimes assumed that nuclear plants cannot change their output within each year or season. Other examples of stylized constraints are e.g., the lowering of variable costs to mimic the avoidance of start-ups (see e.g., [35]), the inclusion of upper limits on the penetration of IRES, or fixing backup or storage requirements (see e.g., [111]). As shown in [115], such stylized constraints possibly overly restrict the deployment of IRES compared to more detailed representations.

Finally, it has to be noted that modeling detailed load-following constraints such as ramping rate restrictions or minimum up and down time restrictions requires chronological data at a sufficiently high resolution. As such, the possibilities to integrate technical constraints are dependent on the temporal representation, i.e., the time-slice division.

An overview of the level of temporal and technical detail typically employed in energy-system optimization models and operational power-system models is presented in a tabular format in Tab. 3.1. For completeness, the typically used level of spatial detail is also presented.

3.2 Literature review on the impact of the temporal and technical detail in long-term planning models

Different authors have recently investigated the impact of the temporal resolution on the model results. A first group analyzes the effect of increasing the temporal resolution on balancing electricity demand and supply (i.e., the dispatch, no investment decisions are considered) [52, 55]. Using a low temporal resolution is shown to lead to an overestimation of the uptake of IRES. A second group analyzes the impact of the temporal resolution on investment decisions [116, 56, 57]. Main results are that by using a low temporal resolution, the optimal level of investments in less flexible baseload technologies and IRES is overestimated, while the optimal level of investments in flexible dispatchable generation technologies is underestimated. Regarding the impact of the level of

Model	Scope	Temporal detail	Technical detail	Spatial detail
Energy-system optimization models	20+ years, multiple energy sectors, single country-multiple countries	4-48 time slices, chronology not always retained	Technology-type level. Individual power plants and their load following constraints as well as system constraints (balancing requirements, inertia, etc.) are typically not considered	Individual countries typically represented by a single node. Cross-border capacity restrictions are typically considered via a trade-based grid representation.
Unit commitment models	$\leq$ 1 year, electrical power sector only, single country-multiple countries	Chronological data an an hourly or lower resolution	Considers individual power plants and corresponding load following constraints as well as reserve constraints	Nodal representation with DC-load flow or trade-based grid representation between countries. Sometimes multiple nodes within each country.

Table 3.1: Overview of the temporal, technical and spatial detail typically used in energy-system optimization models and unit commitment models.

technical detail, Palmintier [8] shows that neglecting operational constraints results in a sub-optimal capacity mix, in turn leading to higher operating costs and carbon emissions. Nweke et al. [117], show in a case study of the South Australian power system that integration of operational constraints in planning models has a significant impact on the investment decisions. Welsch et al. [58] demonstrate in a case study of Ireland that neglecting flexibility requirements strongly impacts the generation portfolio. Finally, van Stiphout et al. [22] show that incorporating reserve requirements in investment planning models can substantially increase the costs of integrating large shares of IRES.

While there is some literature on this topic, the existing literature does not allow answering the question which of the two, the low level of temporal detail or the low level of technical detail, has the highest impact on the model results for multiple reasons. First, the existing literature typically focuses either on the impact of the low level of temporal detail or on the impact of the low level of technical detail. As these different studies are based on very different power systems, the results cannot be easily compared. In addition, in some studies the focus is on the impact on investments, whereas other studies focus on the dispatch.

Second, in the majority of studies focusing on the low level of temporal detail (e.g., [56, 116, 57]), the impact of this level of detail is assessed by comparing the results of a model with a temporal representation typical for long-term planning models with an advanced model that has an increased temporal resolution (i.e., an increased number of diurnal time slices). However, as will be shown in Chapter 4, merely increasing the temporal resolution is not sufficient to have an accurate representation of the temporal dimension. Therefore, the used reference of comparison does not allow quantifying the impact of the temporal representation. In contrast, Haydt et al. [55] do use a correct reference for the temporal representation. Regrettably, in their analysis, the impact of the low level of temporal detail is quantified for a case study of the Flores Island, which is not representative for large interconnected electricity systems. Moreover, electricity generation in the Flores island is based on wind turbines, run-of-river hydro and diesel generators. Due to the fact that there is only one source of fully controllable electricity generation, the impact of the low level of temporal detail on the number of operating hours of different types of generators (baseload, mid-merit, peak load) cannot be analyzed.

Finally, a number of studies presenting novel approaches to bridge the gap between planning and operational models address both the temporal and the technical aspect simultaneously (e.g., [52, 58, 117]). However, the focus in these studies is on evaluating the improvements realized by the presented approach, rather than separately quantifying the impact of the low level of temporal detail and technical detail. A single exception is the work of Deane et al. [52] which allows to some extent to analyze the impact of both aspects separately. However, their analysis is limited to single penetration level of IRES. As will be discussed in Section 3.4 of this paper, the impact of the temporal and technical detail is strongly dependent on the penetration level of IRES.

This work contributes to the existing literature by simultaneously addressing both the impact of the level of temporal and technical detail for a varying penetration of IRES. This allows making the trade-off between improving planning models by extending the temporal detail and/or aiming for a better technical representation.

3.3 Methodology for evaluating the impact of the temporal and technical representation

3.3.1 General methodology

The methodology used to quantify the impact of the low level of temporal and technical detail is based on the soft-linking methodology as described by Deane et al. [52]. The methodology consists of the following steps:

1. Run the long-term planning model for a specific scenario with a gradually increasing penetration of IRES;

2. Extract the results from this model for multiple target years. The results include the installed generation capacity mix (in MW), the annual electrical energy generation shares of each technology and the annual operational costs;

3. Convert the installed capacities of each technology in a number of individual power plants, and provide this input data to the operational UC model. For each type of power plant, provide additional techno-economic characteristics (e.g., minimum stable generation level, minimum up and down times, start-up costs);

4. Provide the original time series for the electricity demand and the availability of IRES for an entire year at an hourly resolution to the operational power-system model, i.e., UC model;

5. Run the UC model without including the detailed technical constraints. Without these constraints, the dispatch in every hour will follow the MO. Therefore this model is referred to as the MO dispatch model in the remainder of this chapter. Compare the results of this model with those of the long-term planning model to analyze the impact of the low level of temporal detail in the long-term planning model;

6. Run the UC model with detailed technical constraints. Compare the results of this model with those of the MO dispatch model to analyze the impact of the low level of technical detail;

7. Repeat steps 5 and 6 for every target year to analyze the relationship between the penetration of IRES and the impact of the low level of temporal and technical detail.

A schematic overview of the methodology applied is presented in Figure 3.2.

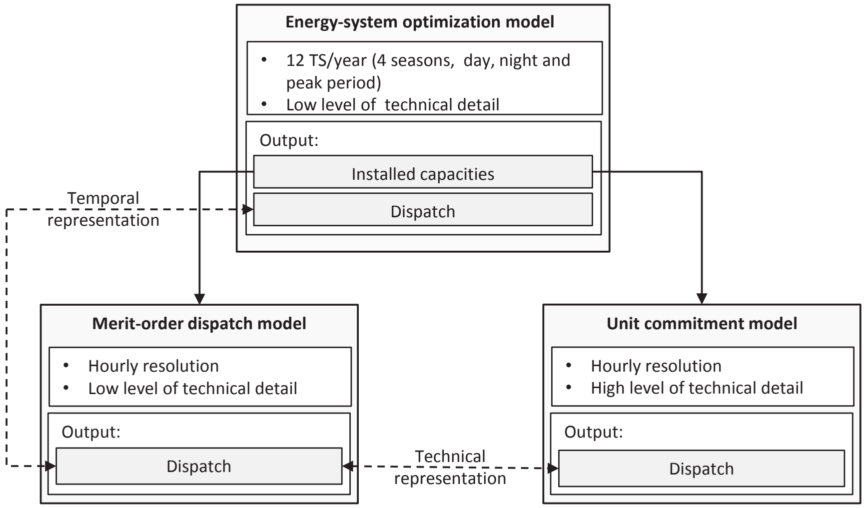


Figure 3.2: Schematic overview of the methodology employed to evaluate the impact of the low level of temporal and technical detail used in energy-system optimization models (ESOMs). The solid lines indicate that the generation capacity mix provided by the ESOM is used as input for the unit commitment (UC) models. The dashed lines indicate the outputs of the different models which will be compared to evaluate the impact of the low level of temporal detail and the low level of technical detail.

3.3.2 Models used for evaluating the impact of the temporal/technical detail.

The long-term planning model used in this work is a TIMES model inspired by the Belgian electricity system. It is assumed here that the Belgian electricity system is representative for other thermally-dominated systems with low potentials for reservoir hydro generation. The time horizon of the planning model is 2014-2055, and is divided into 5 periods. To achieve a varying penetration of IRES throughout the model horizon, a linearly increasing target for the share of annual electrical energy generated by IRES is imposed (0% in 2010, 50% in 2050).

Each milestone year is subdivided in a total of 12 time slices. Four time slices are used to represent seasonal variations. Each seasonal time slice is in turn disaggregated into a day time slice, a night time slice and a time slice corresponding to hours of peak electricity demand[2]. The demand for electricity is assumed to be inelastic and inflexible. Besides the electricity demand, a demand for firm capacity, exceeding the annual peak load by 5%, is imposed in the planning model to ensure generation adequacy. Moreover, in all presented models, network constraints and cross-border trade are disregarded (i.e., island operation with a single node is assumed). Finally, a constant discount rate of 5% is applied.

The mixed integer linear programming (MILP) UC model used in this work is the LUSYM model, developed earlier at KU Leuven. This model determines the optimal scheduling of a given set of power plants to meet the electricity load, taking account of the technical constraints of power plants and the electricity system [49]. The version applied in this work uses hourly time series for an entire year of data and considers the following technical constraints for individual power plants: minimal stable generation level, minimum up and down times, maximum ramping rate, part-load efficiency losses, maintenance requirements, start-up costs and ramp-costs[3]. A full description of this model can be found in [49].

3.3.3 Data for evaluating the impact of the temporal/technical detail.

The set of technology-types considered in this work is restricted to conventional dispatchable power plants, IRES and pumped storage plants. The considered dispatchable technology-types are third generation nuclear power plants (NUCs), supercritical pulverized coal-fired power plant (COAL SC), combined cycle gas turbines (CCGTs) and open cycle gas turbines (OCGTs). The IRES considered are solar photovoltaic (PV) and onshore and offshore wind turbines. The economic and operational characteristics of these technologies are presented in Tab. A.1-A.2 in Appendix A. The investment costs, fixed operations and maintenance (FOM) costs and the efficiency are dependent on the timing of the investment, whereas the other characteristics are assumed to be constant throughout the time horizon. Given the limited geographical potential for additional pumped hydro plants in Belgium, no additional investments in new pumped storage plants are allowed. Moreover, note that combined heat and

[2] As the time slices can be defined freely within the TIMES environment, these time-slice divisions differ to some extent from model to model. Similar time-slice divisions use e.g. 4 seasonal and 2 diurnal time slices, or add a time-slice level to separate weekdays from Saturdays and Sundays.

[3] Given that reserve requirements have their own dynamics and sensitivities, which motivate for an in-depth analysis, operating reserve requirements are not considered in this exploratory chapter. A detailed analysis regarding the impact of operating reserve requirements is presented in Chapter 5.

power (CHP) plants or small generators that might play a more significant role in future energy systems in the context of increasing distributed generation and the implementation of smart grids are not considered.

With the exception of the NUCs, data on investment costs, FOM costs, life times and efficiencies are taken from [111]. Data on nuclear plants and lead times are taken from [118]. VOM costs and technical characteristics of different technologies are adopted from [119]. Regarding IRES, generation profiles for onshore and offshore wind turbines and solar PV panels are taken from measured output in 2013, as provided by the Belgian transmission system operator (TSO) Elia [120]. This generation profile is scaled to the installed capacity in future years. The generation system in the base year (2014), documented by Elia [120], is taken as the current Belgian electricity generation system. The age of the set of existing power plants is assumed to be equally distributed between 0 year and the respective technology-type's lifetime. Similar to the IRES generation profiles, the profile of future electricity demand is considered to be identical to the one observed in 2013 [120]. This profile is scaled using a constant electricity demand growth rate of 1% per year. Changes in the shape of the demand profile, for instance related to the increase in the use of electrical heat pumps or electrical vehicles, are not considered. Fuel prices in the first period are adopted from [118], while fuel price evolutions are derived from [121]. The assumed fuel and emission allowance prices are given in Tab. A.3 in Appendix A.

3.4 Results and discussion

3.4.1 Impact of the temporal and technical representation

Fig. 3.3 presents for each milestone year the electric energy generation shares following from the dispatch in the TIMES model, the MO dispatch model, and the UC model. Differences in dispatch between the TIMES model and the MO dispatch model are solely due to the simplified temporal representation in the TIMES model. The difference between the MO dispatch model and the UC model are due to the low level of technical detail in the MO dispatch model. Furthermore, Tab. 3.2 displays the generation mix error for the different models[4]. As the UC model has the highest level of detail, it serves as a reference for comparison. At this point, it must be stressed that the aim of this work is not to present scenarios for the evolution of the Belgian electricity system, but rather to analyze the impact of the modeling assumptions typically used in

[4]The generation mix error is defined as: $\sum_g \frac{|\alpha_g^{TIMES/MO} - \alpha_g^{UC}|}{2}$, where α_g reflects the generation share of technology g, expressed as a percentage.

long-term planning models. In this regard, our interest lies in the difference in results between the different models, and not in the model results as such.

A first observation is that in the first two periods, there are only slight differences in dispatch. However, as the share of IRES increases, the generation shares in the different models start to diverge. This confirms the presumption that the importance of the temporal representation and the inclusion of operational constraints grows with an increasing penetration of IRES.

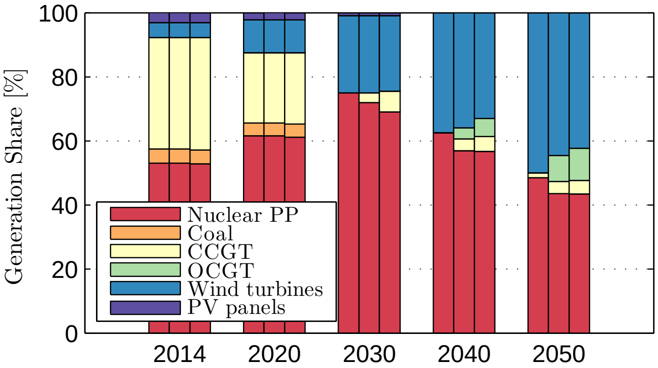


Figure 3.3: Electric energy generation shares for each milestone year in the different models. The left, middle and right bar respectively correspond to the TIMES model, the merit order (MO) dispatch model and the unit commitment (UC) model.

	2014	2020	2030	2040	2050
Generation mix error TIMES [%]	0.4	0.4	6.5	10.2	12.8
Generation mix error MO dispatch [%]	0.4	0.4	3.5	3.1	2.4
Δ generation mix error temporal detail [%]	0.0	0.0	3.0	7.1	10.4
Δ generation mix error technical detail [%]	0.4	0.4	3.5	3.1	2.4
Installed cap IRES/Peak load [-]	0.30	0.42	0.77	1.12	1.49
Installed cap Nuclear/Peak load [-]	0.45	0.52	0.63	0.52	0.42

Table 3.2: Generation mix error and installed capacity ratios in the different models for each milestone year.

Two patterns can be observed in the deviations in dispatch (see Fig. 3.3). First, the share of baseload electric energy generation tends to be overestimated by the TIMES model. Second, this model also systematically overestimates the uptake of IRES. In other words, more curtailment of IRES is required/cost-effective than is anticipated by the TIMES model. A result of this higher level of curtailment is that the proposed portfolio falls short of achieving the imposed target for the share of IRES in the generation mix. An overview of curtailment of IRES and the share of IRES in the generation mix in the different models is presented in Tab. 3.3. From Fig. 3.3, it can be observed that both the temporal representation and the low level of technical detail contribute to the overestimation of baseload and IRES generation. This is in line with the findings of [52, 55, 56, 57].

	2014	2020	2030	2040	2050
Curtailment TIMES [%]	0	0	0	0	0
Curtailment UC [%]	0	0	1.9	11.5	15.4
Share IRES TIMES [%]	7.7	12.5	25	37.5	50
Share IRES UC [%]	7.7	12.5	24.5	33.1	42.3

Table 3.3: Curtailment of intermittent renewable energy sources (IRES) and shares of IRES generation in the energy mix. Curtailment is expressed as a percentage of the maximal IRES generation (i.e., when there is no curtailment). The share of renewable electricity generation is expressed as a percentage of total consumed electric energy.

The operational costs in the different models are presented in Tab. 3.4. The operational costs include fuel costs, costs related to GHG emissions, VOM costs as well as start-up costs. In the case presented here, in comparison to the "most correct" model (i.e., the UC model), the operational costs of the TIMES model are shown to be underestimated by 3-53%, where higher deviations correspond to higher shares of IRES. Again, it can be observed that both the temporal representation and the low level of technical detail contribute to this underestimation of operational costs.

	2014	2020	2030	2040	2050
Operational cost TIMES [EUR/MWh]	29.9	25.2	13.1	10.9	9.4
Operational cost MO dispatch [EUR/MWh]	30.0	25.3	14.5	15.5	17.5
Operational cost UC [EUR/MWh]	30.7	26.0	16.8	18.6	20.1
Impact temporal representation [EUR/MWh]	0.1	0.1	1.4	4.6	8.1
Impact technical detail [EUR/MWh]	0.7	0.7	2.3	3.1	2.6

Table 3.4: Operational costs in the different models for each milestone year. All costs are expressed relative to the total consumed electric energy.

When these model simplifications are applied in models used for analyzing transition pathways towards more sustainable energy systems with high shares of IRES, all the above-mentioned errors occur simultaneously. That is, the operational costs are underestimated, the uptake of IRES will be overestimated and the level of baseload generation will be overestimated. It must be noted that the main strength of TIMES models, and ESOMs in general, is their ability to explore the transition of the entire energy system rather than presenting a detailed analysis of the electricity sector. Nevertheless, given the critical role the electrical power system is expected to play in the transition of the entire energy system, the model simplifications made in modeling the operation of the electrical power system will likely lead to a considerable underestimation of the efforts required to effectively obtain a desired reduction of GHG emissions or renewable energy sources (RES) penetration[5]. It must be stressed here that in the presented analysis, the flexibility that can be provided by having a more interconnected system, investments in additional electrical storage technologies or by an active demand response are not considered. When these flexibility options would be included, the impact of the low level of temporal and technical detail would likely become lower.

However, regardless of the magnitude of the impact on the operational costs (and total system costs), models using these model simplifications tend to overly value intermittent and inflexible generation, while not providing sufficient incentives for different flexibility options. This creates a bias towards certain technologies which is particularly important as this type of models commonly serves as a base for underpinning policy regarding R&D of innovative energy technologies. It must therefore be concluded that the model simplifications typically used in long-term planning models can no longer be justified when analyzing systems with high shares of IRES.

3.4.2 Temporal versus technical detail

To improve these planning models, one could either adapt the temporal representation or increase the level of technical detail. This section analyzes the impact of the individual model simplifications, thereby aiming to provide guidelines as to which aspect should be addressed with the highest priority.

From Tab. 3.2 and Tab. 3.4, it can be seen that for a *low penetration of IRES*, the impact of the level of technical detail is higher than the impact of the temporal representation, both in terms of the impact on the generation mix and

[5]Note that we only discussed the operational costs here. In systems with a high penetration of IRES, the operational costs can become significantly smaller than the investment and FOM costs.

in terms of the impact on the operational cost. For penetration levels of IRES up to 12.5% in terms of yearly electric energy generated, the impact of both model simplifications is limited. When the IRES penetration reaches a level of 25%, the impact of both model simplifications has risen significantly, and is similar in terms of impact on the generation mix. Regarding the operational cost, the level of technical detail has the highest impact on the results. However, for *higher shares of IRES*, the impact of the temporal representation increases strongly, while the impact of the low level of technical detail starts to stagnate and even decreases. As a result, for high penetrations of IRES, the temporal representation becomes the dominant factor.

The impact of the temporal representation can be explained by analyzing how it accounts for the variability of IRES generation. Fig. 3.4 displays how the load duration curve (LDC), the wind generation duration curve and the residual load duration curve (RLDC)[6] are approximated by the TIMES model using 12 time slices in model year 2050. This figure clearly illustrates that, while the temporal representation using 12 time slices approximates the LDC with reasonable accuracy, this is not the case for the wind generation duration curve, and hence not for the RLDC.

The main idea behind using time-slice trees as the one considered here is to capture the significant seasonal and diurnal differences between different time slices. The inherent assumption is that the data in different time slices is significantly dissimilar (e.g., electricity demand in peak and night time), while different data values that fall within each time slice are similar (e.g., electricity demand in all peak periods). As the load profile has strong regularities, both on the seasonal, daily and diurnal level, time-slice divisions such as the one considered here obtain a relatively good representation of the load profile. In contrast, due to the lack of regularities in wind-power fluctuations, averaging the wind-turbine electricity generation data belonging to a specific time slice (e.g., all wind data corresponding to periods of peak electricity demand during the entire winter) causes periods of very high or very low wind generation to be overlooked. This is reflected in the relatively flat approximation of the wind generation duration curve (see Fig. 3.4b). This is corroborated by the literature. For instance, in the documentation of the JRC-EU-TIMES model, the reported capacity factors for wind technologies in Belgium vary between 6% and 21% for

[6]The residual load for each time interval is found by subtracting the potential undispatchable electricity generation in that time interval from the load corresponding to that time interval. The only undispatchable electricity generation considered here is the electricity generation by wind turbines and solar PV panels. Moreover, the term "potential electric energy generation", as opposed to the actual electric energy generation, is used to account for the fact that the actual electric energy generation can be lower than the potential electric energy generation in a specific time slice in case of curtailment. Sorting this residual load from high to low gives the RLDC.

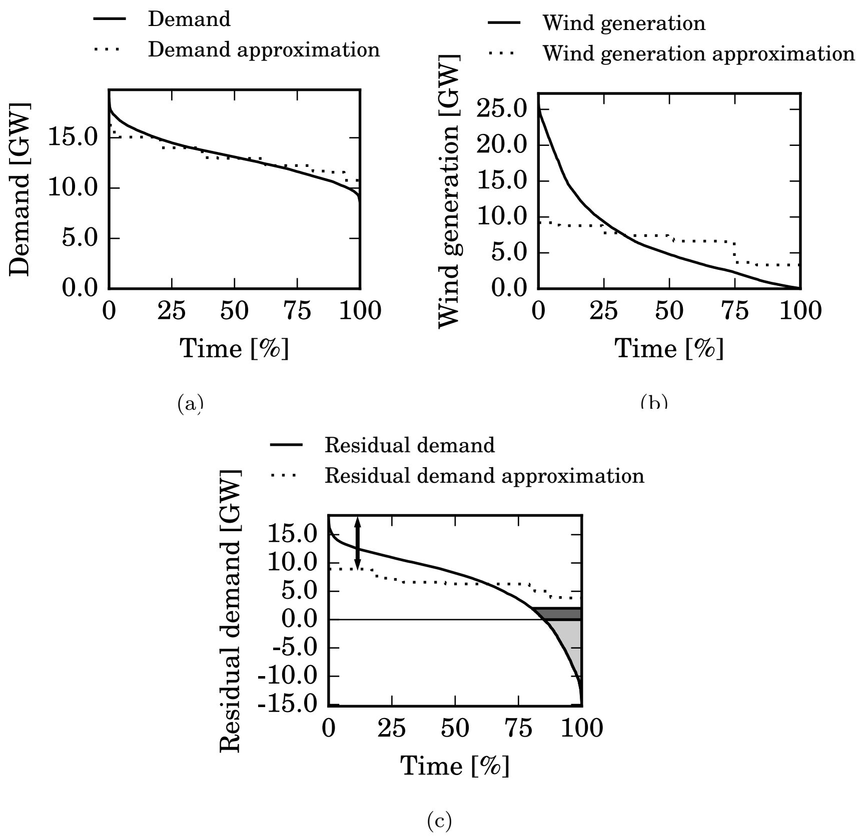


Figure 3.4: Approximation of the load duration curve (LDC) (a), the wind generation duration curve (b) and the residual load duration curve (RLDC) (c) for model year 2050 in the TIMES model using 12 time slices (dotted lines). The reference (solid line) corresponds to the sorted hourly data for an entire year. The arrow in (c) indicates the underestimation of the peak residual load. The light grey area indicates the underestimation of excess energy. The dark grey area illustrates how the number of operating hours of baseload technologies can be overestimated.

the different time slices. For solar technologies, there are more regularities on seasonal and diurnal level and these effects will be less pronounced.

As can be observed in Fig. 3.4c, this method of time-slicing will also result in an approximation of the RLDC which is too flat. Different authors have highlighted the significance of the RLDC for the investment planning problem [122, 123, 14]. This because the RLDC contains information about key aspects related to the integration of IRES, such as the low capacity credit of IRES, the impact of IRES on the number of operating hours of thermal power plants, and the amount of excess energy (possibly leading to curtailment) [122]. To capture these aspects, it is important that the temporal representation approximates the RLDC with high accuracy.

First, as illustrated by the arrow in Fig. 3.4c, the approximation of the RLDC in the model employing 12 time slices causes a considerable underestimation of the peak residual load as these peaks occur when IRES power generation is very low and the load is high, i.e., the capacity credit of IRES is overestimated. In this regard, the role of the constraint demanding sufficient firm capacity is crucial to obtain generation portfolios which can achieve a reasonable security of supply[7]. However, while such constraints ensure sufficient firm capacity and result in *investments* in peak-load technologies, such constraints are not sufficient to account for the effective *use* of these peak-load technologies and the related fuel costs and emissions.

Second, the residual load in periods of high IRES generation is overestimated. This results in an overestimation of the number of full load hours that can be obtained by baseload technologies, as indicated by the dark grey area in Fig. 3.4c.

Finally, periods of excess electrical energy generation might be overlooked, causing an overestimation of the potential uptake of IRES electricity generation, as illustrated by the light grey area in Fig. 3.4c.

In terms of costs, the 12-slice TIMES model results in an underestimation of operational costs, as overestimating the share of baseload generation and IRES generation leads to an underestimation of electricity generation by more expensive mid-merit and peak-load technologies (see Tab. 3.4). As can be observed from Tab. 3.2 and Tab. 3.4, the impact of a temporal representation that does not properly account for the variability of IRES generation grows strongly with the share of IRES.

Understanding the impact of the level of technical detail is more complex for multiple reasons. First, what is referred to as the level of technical detail here bundles a variety of different technical constraints (e.g., ramping rate restrictions, minimum up and down times) as well as economic operational characteristics (e.g., start-up costs, part-load efficiency losses), all having

[7]It must be noted that in such constraints, the capacity credit given to thermal generators, storage technologies as well as IRES is provided exogenously. Hence, the actual contribution of IRES to ensuring generation adequacy can be corrected for via these constraints

a different impact. Second, in contrast with the impact of the temporal representation, the penetration level of IRES is no longer the only driver for differences in the dispatch. That is, also the flexibility of the thermal generation fleet plays a role[8]. Whereas the penetration of IRES determines the volatility of the residual load, the possibilities to satisfy this fluctuating residual load are determined by the flexibility of the generation fleet. Moreover, in the long term, the penetration of IRES and the flexibility of the thermal generation fleet are interdependent. With an increasing share of IRES, the number of full load hours of baseload technologies is reduced. Therefore, one could expect that the fraction of baseload capacity, which is generally less flexible, is reduced as the penetration of IRES increases over time. As a result, the generation fleet will likely become more flexible as the penetration of IRES increases. This can also be observed in the results of the planning model from 2030 onwards, where the installed capacity of nuclear plants is reduced (see Tab. 3.2). Before 2030, the nuclear capacity is increased despite the fact that there is an increasing penetration of IRES. This is due to the fact that the model starts from the existing Belgian capacity mix which, according to the data used in this work, contains a suboptimally low level of nuclear plants. Due to the lead times of building new plants, and the gradual retirement of existing capacity, the capacity of nuclear plants cannot instantly be increased.

If the penetration of IRES is low, it can be observed from Tab. 3.2 that the level of technical detail has little impact on the generation mix. This is due to the fact that the variability of the residual load is still limited, and the technical constraints do not become binding, i.e., there is excess flexibility. As a result, there is little need to deviate from the MO (see Fig. 3.3). However, in terms of operational costs, there will always be plants which need to cycle (i.e., change the power output by ramping up/down or by switching on/off), thereby incurring start-up costs, ramping costs and additional fuel and emission costs due to efficiency losses in part-load operation. Up to 2020, these costs are responsible for over 50% of the underestimation of the operational costs due to the low level of technical[9].

As the penetration of IRES, and therefore, the variability of the residual load, increases, there will be an increased need for cycling. Moreover, due to the large fraction of electrical power generated by IRES in some moments, there

[8]The impact of the different technical constraints and economic operational characteristics, as well as the dependence on the flexibility of the generation fleet is investigated in detail in Chapter 5.

[9]This only includes the direct costs related to start-ups, ramping and part-load efficiency losses. In some situations, the knowledge of start-up and ramping costs will incur indirect costs, e.g., more expensive generation can be brought/kept on line to avoid the high start-up costs for bringing online a large baseload/mid-merit unit when little additional capacity is required. Such indirect costs are not included in the percentage of costs reported here.

will be an increased need for cycling of baseload and mid-merit power plants.

On the one hand, these baseload plants are generally less flexible, and the technical constraints for these plants can become binding[10]. In these cases, the dispatch proposed by the TIMES model and the MO dispatch model might be technically infeasible, and the UC model will be forced to schedule additional flexible generation and/or to curtail IRES generation. The result of neglecting these technical constraints is an overestimation of the generation by baseload technologies and an overestimation of the uptake of IRES generation.

On the other hand, the dispatch of the UC model might deviate from the dispatch in the MO model to avoid start-up costs, i.e., the dispatch proposed by the MO model might be technically feasible but not optimal when start-up costs are accounted for. Regarding the uptake of IRES generation, this might lead to additional curtailment, as it can be more economic to curtail some IRES generation than to shut down a plant which would have to be brought online again some hours later. Regarding baseload generation, the impact of accounting for start-up costs is twofold. Baseload plants might be kept on line to prevent start-up costs some hours later, thereby leading to curtailment of IRES. Alternatively, baseload plants might be kept offline to avoid the high start-up costs.

For the year 2030, the impact of the level of technical detail has increased significantly with respect to the first two periods. This is due to the fact that both the IRES penetration and the share of baseload capacity have increased with respect to 2014. While for the first two periods, hardly any impact on the generation shares could be observed, this is no longer the case in 2030. In terms of operational costs, a strong increase in the underestimation of operational costs can be observed. Whereas the start-up costs, ramping costs, and costs related to part-load efficiency losses were responsible for over 50% of the underestimation of operational costs in the first two periods, this share has dropped to less than 20% in 2030, indicating that it is mainly the switch to an increased generation by more flexible, but more expensive CCGTs, which has caused the increased underestimation of operational costs.

Further increasing the share of IRES will further increase the need for cycling. However, it can be observed that, from 2040 onwards, the capacity of less-flexible nuclear plants is reduced. As a result, the impact of the low level of technical detail starts to stagnate, and is even slightly reduced by 2050 (see Tab. 3.2 and Tab. 3.4). In this regard, it must be noted that the capacity mix used as input in the UC model corresponds to the solution of a planning

[10] Technically, baseload plants, such as nuclear power plants, are capable of cycling; however, if not forced to by market or regulatory circumstances, operators prefer to run them at constant power output.

model with a low level of temporal detail, which, as discussed above, causes the potential of baseload technologies to be overestimated. Therefore, the impact of the low level of technical detail would likely be even lower when the temporal representation would be improved. Moreover, CHP plants and small generators were not considered in the analysis. Nevertheless, these types of generation can provide a significant source of generation flexibility and could therefore reduce the impact of the low level of technical detail even further.

It can be concluded that for a low penetration of IRES, both the low level of temporal and the low level of technical detail have a limited impact on the results. As the penetration of IRES increases, also the impact of the temporal representation and the low level of technical detail start to increase. However, whereas the impact of the low level of technical detail starts to stagnate for even higher penetrations of IRES (as a high penetration of IRES gives rise to a more flexible generation fleet), the impact of the temporal representation keeps increasing. For IRES penetration levels of 35-50%, in terms of yearly electric energy generated, the impact of the temporal representation is shown to be significantly higher than the impact of the level of technical detail, which seems to be in line with the results presented in [52]. For this reason, improving the temporal representation in planning models is suggested to be prioritized.

3.5 Summary and conclusions

The highly variable and stochastic nature of intermittent renewable energy sources (IRES) poses challenges to the operation of the electrical power system which might not be reflected in long-term energy-system optimization models, as these models typically use a low level of temporal and technical detail. This chapter has examined the impact of the low level of temporal and technical detail. A detailed modeling analysis has been set-up to quantify the impact of both the temporal and technical representation typically used in energy-system optimization models (ESOMs) for a varying penetration of IRES.

Both the low level of temporal and technical detail are shown to have the same qualitative impact on the results, i.e., a low level of detail results in an overestimation of the potential uptake of IRES, an overestimation of the generation by baseload technologies and an underestimation of operational costs. While for a low penetration of IRES, the impact of both the temporal representation and the low level of technical detail is limited, the impact of the temporal representation becomes dominant for a high share of IRES electric energy generation (35-50%). We therefore recommend prioritizing addressing the temporal representation.

The high impact of the temporal representation is shown to result from the fact that the typical use of time slices involves averaging the instantaneous generation of IRES. As a result, the variability of IRES (for wind energy in particular), and the corresponding impact on the operation of the system are not well captured.

Chapter 4

Improved temporal representation in planning models

This chapter focuses on methods to improve the temporal representation in long-term energy-system optimization models (energy-system optimization models (ESOMs)) and electrical power-system optimization models (power-system optimization models (PSOMs)). As shown in Chapter 3, the time-slice divisions typically used in large-scale ESOMs do not accurately reflect the variability of intermittent renewable energy sources (IRES), typically leading to an underestimation of the operational costs and an overestimation of the uptake of IRES and the value of baseload technologies. Growing awareness of this issue has led researchers to experiment with different time-slice divisions.

The first goal of this chapter is to provide an overview of different time-slicing methods that could be used to represent intra-annual variations in demand and supply, and evaluate their respective strengths and weaknesses. While much attention in the literature has gone to increasing the temporal resolution and hence the number of time slices (see e.g., [56, 54, 55, 116, 124, 125, 126]), the work presented here takes a broader perspective and evaluates fundamentally different methods to represent the temporal dimension. One of the time-slicing methods which will be shown to have the potential to strongly improve the temporal representation is based on using the data of a limited number of representative historical periods (e.g., days or weeks). However, as will be shown, the quality of this time-slicing method is strongly dependent on the selected historical periods. Therefore, the second main goal of this chapter is to assess different methods to select a set of representative historical periods. In this regard, a new optimization-based approach is developed and compared to methods available in the literature.

The remainder of this chapter is organized as follows. First, Section 4.1 presents a description of different time-slicing methods that have been deployed, or that are similar to methods that have been reported in the literature. These different time-slicing methods are subsequently evaluated in Section 4.2. Next, Section 4.3 assesses different methods that can be used to select a representative set of historical periods. Finally, the main conclusions are formulated in Section 4.4.

This chapter is based on:

- Poncelet, K., Höschle, H., Delarue, E., Virag, A., and D'haeseleer, W. *Selecting representative days for capturing the implications of integrating intermittent renewables in generation expansion planning problems.* IEEE Transactions on Power Systems 32, 3 (May 2017), 1936–1948.
- Poncelet, K., Delarue, E., Six, D., Duerinck, J., and D'haeseleer, W. *Impact of the level of temporal and operational detail in energy-system planning models.* Applied Energy 162 (Jan. 2016), 631–643.
- Collins, S., Deane, J. P., Poncelet, K., Panos, E., Pietzcker, R. C., Delarue, E., and Ó Gallachóir, B. *Integrating short term variations of the power system into integrated energy system models: A methodological review.* Renewable and Sustainable Energy Reviews 76, Supplement C (2017), 839 – 856.

4.1 Overview of time-slicing methods

This section provides an overview of different time-slicing methods that have been used to represent intra-annual variations in demand and supply in long-term planning models. First, two different time-slicing methods which have been commonly used will be discussed. Following Haydt et al. [55], we will refer to these methods as the Integral method and the semi-dynamic (SD) method. Next, different adaptations to these methods will be presented that have been developed to cope with the variability of IRES.

4.1.1 Integral time-slicing method

The integral time-slicing method is the oldest and simplest method to capture intra-annual variations in the electricity demand. In this method, typically 5-10 time slices are used to distinguish between different load levels occurring throughout the year, as visualized in Fig. 4.1. Each time slice thus represents an average load level during a certain fraction of the year. This method has been for instance used in the LEAP model [55].

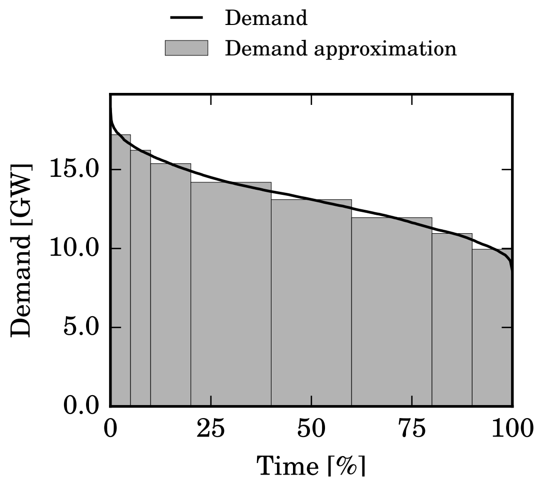


Figure 4.1: Graphical illustration of the integral time-slicing method. Each bar represents a single time slice.

In this method, all chronological information is lost as different load levels can occur at different moments in time. Due to the loss of chronology, average IRES capacity factors are used [55]. As such, this method does not reflect the main challenge related to the integration of IRES, namely that there will be periods of very high IRES generation and periods during which there is virtually no IRES generation. Therefore, this time-slicing method is not suited to analyze the transition towards electricity systems with high shares of IRES. In addition, the dynamics of variations in demand (and supply) are not captured since the chronology is not preserved. Therefore, the value of storage systems and other flexibility options cannot be determined.

4.1.2 Semi-dynamic time-slicing method

The semi-dynamic (SD) method is the most commonly used time-slicing method and has been introduced in Chapter 3. In this method, a year is disaggregated into different seasons, days of the week and/or diurnal periods. The value assigned to the load and IRES availability in each time slice corresponds to the average value of those parts of the time series corresponding to that time slice. Depending on the number of seasonal, daily and diurnal time slices used, the total number of time slices typically varies between 4 and 48. This method has been, among others, applied in MARKAL/TIMES models (see e.g., [111, 32, 124, 52, 54]), OSeMOSYS models (see e.g., [127, 128]) and NREL's ReEDS model [84].

Under the assumption that the time series for different loads (e.g., heat and electricity) as well as (to some extent) IRES generation have reasonably regular patterns on a seasonal, weekly and daily time scale, this method does allow capturing the basic variations in both the demand and the availability of IRES. In addition, this approach to time slicing preserves chronology. Therefore, in principle, this method allows capturing the challenges related to short-term dynamic variations in demand and supply. Additionally, the preservation of chronology allows endogenously valuing storage systems and other sources of flexibility.

However, as shown in Chapter 3, the time series of IRES, and wind in particular, do not follow highly regular patterns on a seasonal, weekly and daily time scale. As a result, the averaging smooths out IRES, i.e., periods of very high and very low resource availability will be overlooked. Therefore, this time-slicing method does not sufficiently capture the variability of IRES (and the resulting impact on the operation of the power system).

4.1.3 Semi-dynamic time-slicing method with increased resolution

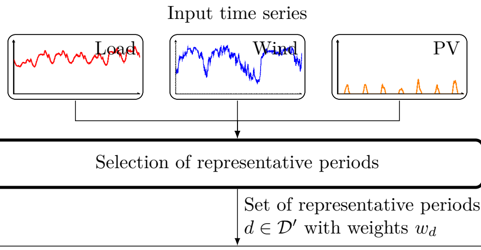
Starting from the premise that balancing supply and demand of electricity in the short term becomes more challenging in systems with a high penetration of IRES, a number of authors have experimented with increasing the number of time slices (see e.g., [56, 54, 55, 116, 124, 125]). More specifically, the focus has predominantly been on increasing the number of diurnal time slices, i.e., the temporal resolution. Pina et al. [56] increase the number of time slices used in a TIMES model for Sao Miguel (Azores, Portugal) to 288 by considering 4 seasons, 3 types of day per season (weekday, Saturday, Sunday) and 24 hours per day. By varying the number of diurnal time slices, they show that the used resolution impacts results. More specifically, fewer investments in wind turbines are observed when the resolution is increased, indicating that it is more difficult/costly to integrate wind generation. Similar results are obtained from an analysis for the Swiss power system using the Swiss TIMES electricity model (STEM–E), where the results of a model using 288 time slices were compared to those of a model using only 8 time slices [125]. However, as will be shown in Section 4.2, increasing the resolution only avoids the averaging of IRES generation patterns to a limited extent.

4.1.4 Semi-dynamic time-slicing method with representative days

As discussed above, using the SD method with a limited number of time slices can lead to averaging of IRES generation, thereby strongly underestimating the variability of IRES generation. One way of avoiding this averaging is to select a set of historical days to represent an entire year and to use the data of these days directly in the time slices. Each selected day then represents a part of the year (e.g., a season, a month or simply a certain fraction of the year)[1]. These representative days can in turn be divided into a number of diurnal time slices. As such, the value assigned to each time slice is not the result of taking an average over multiple days.

Fig. 4.2 illustrates the concept of using a representative set of historical periods (e.g., days or weeks) in ESOMs/PSOMs. As is illustrated in this figure, from different time series (e.g., quarter-hourly load, wind and solar generation data of multiple years), a number of representative periods are selected and each selected period is given a certain weight (i.e., the number of times the representative period is assumed to be repeated within a single year. The data of the representative periods and the weights given to these representative periods is then fed into the ESOM/PSOM. A highly simplified mathematical description of such a ESOM/PSOM is shown. Here, a balance of generation (gen) and demand (DEM) is imposed in every time step t (e.g., quarter-hour) of every selected period d. The power generation $gen_{g,d,t}$ by every technology/plant g is restricted by the installed capacity (cap_g). The fixed costs relate to the construction and fixed operations and maintenance of this capacity. Variable costs, comprising fuel costs, variable operations and maintenance (VOM) costs and taxes are related to the generation levels of every technology/plant in the selected periods. The weights of each representative period are used to scale the variable costs incurred in the selected periods to an equivalent annual cost.

[1] Although this method selects specific periods of the original time series rather than slicing the entire time series into different blocks, we will refer to this method of representing the temporal dimension as a time-slicing method within this text.



Energy-system optimization model (ESOM) /
Power-system optimization model (PSOM)

$$\min_{cap,gen} fixedcost + variablecost,$$

$$s.t.$$

$$fixedcost = FC_g cap_g$$

$$variablecost = \sum_{d \in \mathcal{D}'} \Big(w_d \sum_{g,t} (VC_g gen_{g,d,t} \Delta_t) \Big)$$

$$gen_{g,d,t} \leq cap_g \quad \forall g, d, t$$

$$\sum_{g} gen_{g,d,t} = DEM_{d,t} \quad \forall d, t$$

$$\ldots$$

Figure 4.2: Schematic of the use of a set of representative historical periods in energy-system optimization models (ESOMs) or power-system optimization models (PSOMs).

Similarly, fuel consumption and emissions during the selected periods can be scaled to equivalent annual amounts. Thus, the representative set of periods is used to endogenously determine a good approximation of the amount of electricity that is generated by different technologies/units and the associated costs, emissions and fuel use without requiring to optimize the operations over an entire year.

This method of using representative periods has, among others, been applied in the POTEnCIA model recently developed by The Institute for Prospective Technological Studies (IPTS) of the European Commission's Joint Research Centre [129], the US-REGEN model developed by the Electric Power Research Institute (EPRI) [69] and a number of power-system optimization models, such as MIT's Investment Model for Renewable Electricity Systems (IMRES), the Switch model [86, 112], the LIMES-EU model developed by the Potsdam Institute of Climate Impact Research [85], NREL's Resource Planning Model

(RPM) [87, 130] and the model developed by Jin et al. [131].

To illustrate the difference between the traditional SD method and the variant using representative days, consider a model with 4 seasonal time slices and 3 diurnal time slices (day, night and peak). Figure 4.3 visualizes the process of assigning a value to the time slice representing periods of peak demand during the winter for both methods. The graphs on the left hand side show time series of the load, the residual load and onshore wind generation during a winter week for an exemplary system with a high penetration of wind power. Every day of the entire season, samples are taken during the peak hours (lasting 2 hours in each day). The graphs on the right hand side display all the samples taken during the entire winter season (91 days). The blue lines in the right-hand side panels indicate the values assigned to the winter peak time slice in the traditional SD method, i.e., the average value of all samples. Following the variant using representative days, the value assigned to the winter peak time slice corresponds to the average value of the samples corresponding to the single day selected to be representative for the winter season. Hence, the value can lie anywhere in the shaded intervals, depending on which day is selected. The red lines in the right-hand side panels indicate the values assigned to this time slice if the sample displayed in red in the left-hand side panels would be selected.

Note that whenever it is not necessary to stick to time slices defined according to different seasons and days in the week, one can select a set of days which are representative for the year without having to define days which are representative for a season, month or a certain day in the week within that season/month. In this case, each individual day is not representative of anything in particular. Rather, the set of selected days aims to be representative for an entire year.

The advantage of the method using representative days is that smoothing is avoided and hence both the IRES generation and the demand can be anywhere within the ranges actually observed, and hence, the variability can be captured. In addition, chronology is preserved. However, the main issue with this approach is the difficulty of selecting a set of days which is representative for an entire year (or multiple years).

4.1.5 Enhanced integral time-slicing method

A different way to overcome the issue of leveling out IRES generation by taking the average over periods of high and low resource availability is to explicitly account for periods of high and low IRES. To do so, one could for instance start from the traditional SD method and add an additional time-slice level which represents the availability of IRES, where different time slices represent different ranges of IRES availability. This method would still average IRES availability

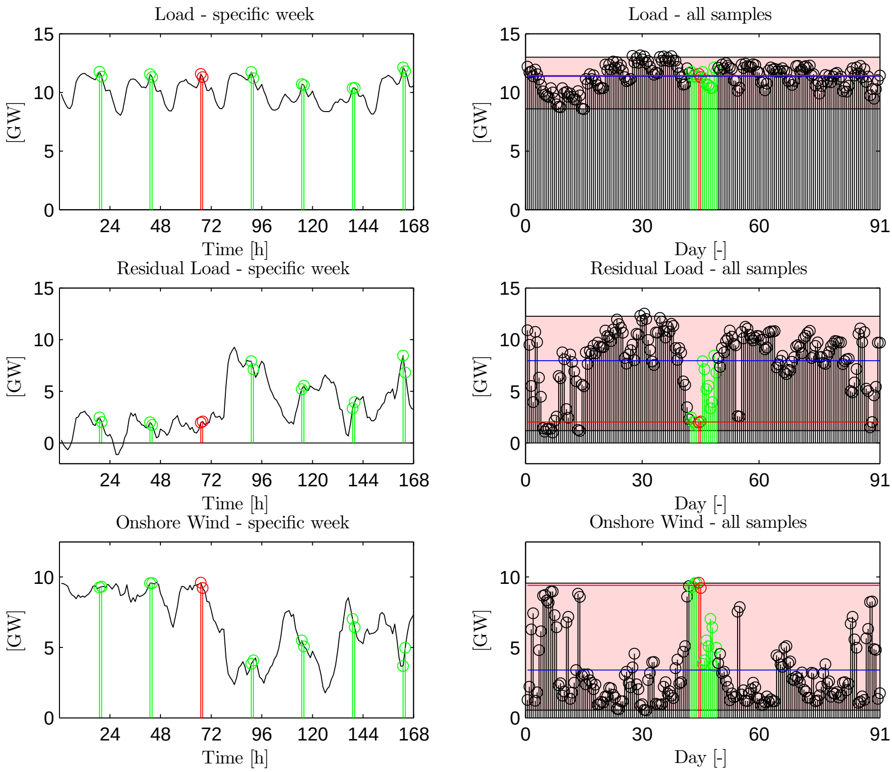


Figure 4.3: Process of assigning values to time slices using the traditional semi-dynamic (SD) time-slicing method and the SD time-slicing method using representative days.

over samples from multiple historical days, but now the average would only be taken over a subset of samples with similar resource availabilities (e.g., the 20% of samples corresponding to the highest wind generation within the parent time slice). Such an approach has been hinted at by Kannan and Turton [113] and has been recently adopted in the POLES model [68].

A drawback of this approach is that the chronology is lost since no information is retained regarding how frequent and how fast the IRES availability changes[2]. Therefore, the dynamics of the system and the corresponding value of flexibility options, such as storage systems, cannot be represented [132]. The importance

[2]Note that it is still possible to capture chronological variations on longer time scales such as seasons.

of retaining chronology for the cost-optimal evolution of the South-Australian power system is analyzed in [58], where the results of a model with and without chronology were compared. In the presented case of that Australian study, differences in the capacity mix were shown to be significant. The model that retains chronology is shown to invest less in IRES and baseload technologies and more in flexible thermal power plants. However, the total system cost resulting from the capacity expansion plans obtained using the model with and without chronology were shown to be very similar for the presented case.

Given that chronology is lost when an additional time-slice level corresponding to different resource availabilities is added, we argue that it would be more efficient to not consider the time slices used in the traditional SD method which are based on the time of the year, week or day. Instead, one could expand the integral method (which defines time slices based on the load level) by not only distinguishing explicitly between different load levels occurring throughout a year but by simultaneously accounting for different levels of IRES generation. As such, the time-slice division forms a discrete representation of the joint probability distribution of the load and IRES availability. This is visualized in Fig. 4.4 for a model in which 3 load levels and three levels of wind availability are considered[3]. In the remainder of this text, we will refer to this method as the enhanced integral (EI) method. Up to the best of our knowledge, a time-slice division following this method has not yet been used in planning models. Very recently however, a similar time-slice division in which the distribution of wind and solar resource availabilities are sliced has been used in the GET model. In that model, 10 time slices were used to capture the joint probability distribution of wind and solar resources [133].

[3]Note that this approach is not restricted to approximating the joint probability distribution of two time series. The method can easily be applied to capture the joint probability distribution of any given number of time series.

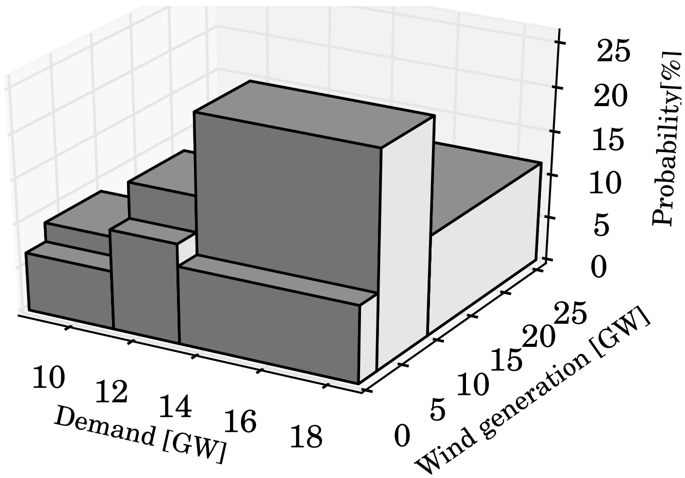


Figure 4.4: Graphical illustration of defining time slices in the enhanced integral (EI) method. Each block in the figure represents a specific time slice. The width and depth of the block respectively represent the range of load and wind generation values corresponding to that time slice. The height of the block represent the duration of the time slice (expressed as a fraction of the year or a probability of occurence). Note that the load and wind values that are finally assigned to a specific time slice are the average values of the load and wind generation time series falling within the ranges spanned by that time slice. These values are not presented in the figure.

4.2 Evaluation of time-slicing methods

The aim of this section is to evaluate the different time-slicing methods presented in the previous section.

4.2.1 Methodology

Six different time-slice divisions will be compared. For both the SD time-slicing method, the SD time-slicing method which uses representative days, and the EI time-slicing method, a time-slice division using a *low* number of time slices and a time-slice division using a *high* number of time slices are created, and the results are compared. An overview of all considered time-slice divisions is presented in Tab. 4.1. For the time-slice divisions using representative days, 10,000 samples of respectively 2 and 12 randomly selected days are taken. Each selected day is assumed to represent an equal fraction of the entire year.

Temporal representation	Number of time slices					
	Seasonal	Daily	Diurnal	Load	IRES	Total
SD low	4	-	3 (day, night, peak)	-	-	12
SD repr. days low	2	-	6 (4-hourly resolution)	-	-	12
EI low	-	-	-	3	4	12
SD high	4	3 (Weekday, Sat, Sun)	24	-	-	288
SD repr. days high	12	-	24	-	-	288
EI high	-	-	-	17	17	289
Reference	-	-	-	-	-	8760

Table 4.1: Overview of the considered different time-slice divisions.

The main criterion used to evaluate the accuracy of these different time-slice divisions is the quality of the approximation of the residual load duration curve (RLDC). The root-mean-square error (RMSE) of the RLDC (expressed relative to the peak load) is taken as the metric for the quality of the approximation. An entire year of data at hourly resolution serves as the reference. To analyze the impact of the penetration level of IRES, five different penetration levels of wind are considered. Aside from approximating the RLDC, other important temporal aspects, such as whether or not chronology is retained, are discussed qualitatively.

The load and wind time series used correspond to the data reported for the Belgian system for 2013. All data is provided by the Belgian transmission system operator (TSO) Elia [134].

4.2.2 Results and discussion

Approximation of the residual load duration curve

Fig. 4.5 shows, for each considered time-slice division, the accuracy of the approximation of the residual load duration curve (RLDC) as a function of the wind-energy penetration. For the time-slice divisions using representative days, the boxplots present the distribution of the accuracy for 10,000 samples of randomly selected days. In addition, Fig. 4.6 displays the approximation of the RLDC, the load duration curve (LDC) and the wind generation duration curve (DC) of the different time-slice divisions for a case where the installed capacity of wind turbines equals 1.2 times the peak load. In this figure, the approximation of the SD time-slice divisions using representative days is based on the sample of days which best approximates the RLDC.

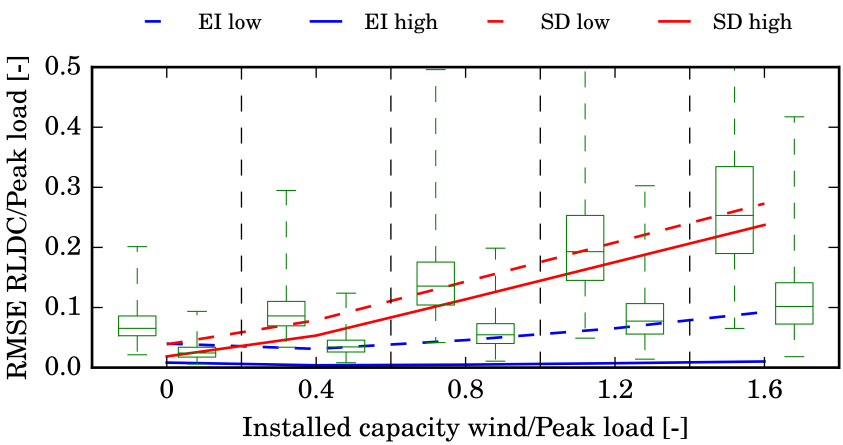


Figure 4.5: Approximation error of the residual load duration curve (RLDC) for different time-slice divisions and a varying wind-energy penetration. The left and right boxplots corresponding to each wind-energy penetration case present the distribution of the approximation errors of the RLDC for 10,000 random samples of 2 and 12 days, respectively. The median, the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentile (rectangle), as well as the highest and lowest errors obtained (whiskers) are shown. All approximation errors are expressed as the root-mean-square error (RMSE) relative to the peak demand. The acronyms SD and EI refer to the semi-dynamic and the enhanced integral time-slicing methods, respectively.

Figs. 4.5 and 4.6 show that, relative to the traditional SD time-slice division with a low number of time slices (SD low), increasing the resolution (SD high)

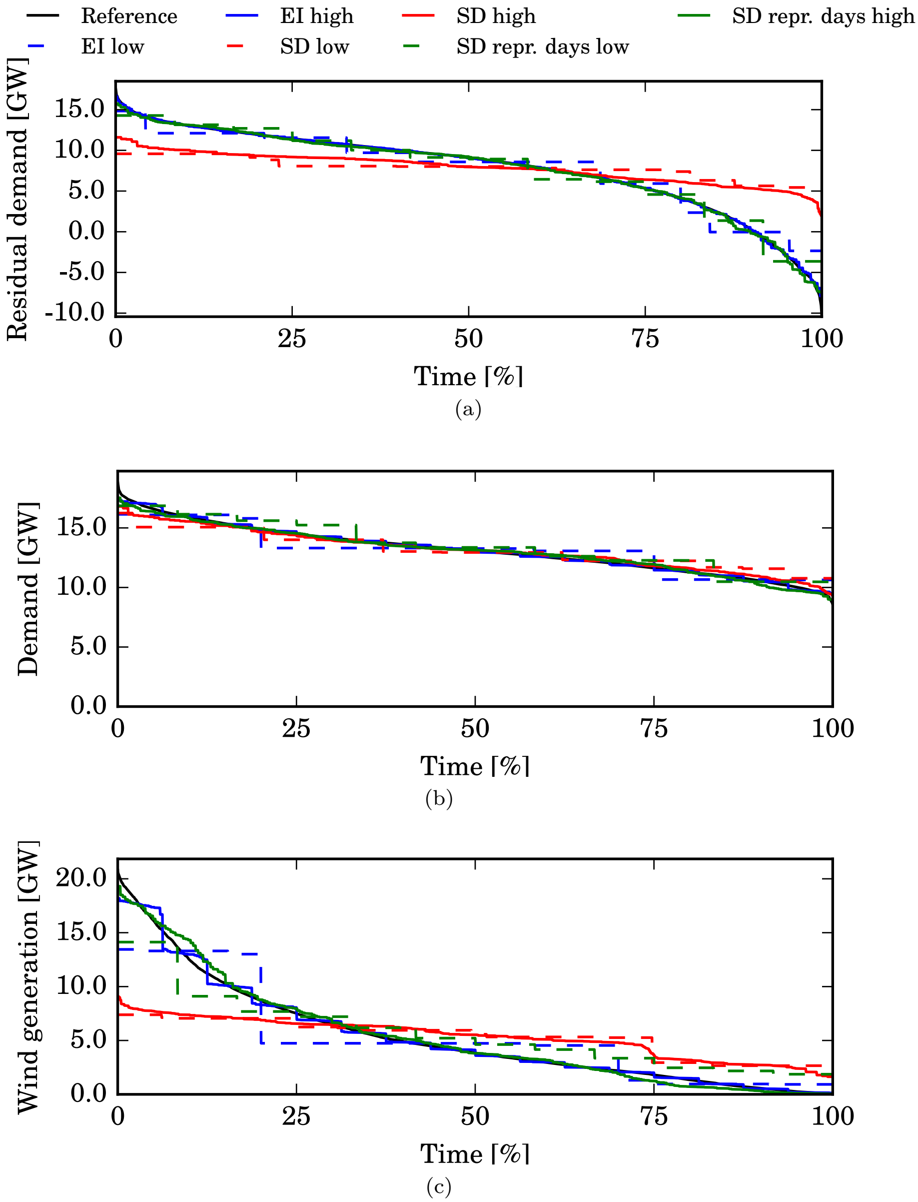


Figure 4.6: Approximation the residual load duration curve (RLDC) in the case where the installed wind capacity is a factor 1.2 higher than the peak load (a), the load duration curve (LDC) (b) and the wind generation DC (c) for the different time-slice divisions. The DCs of the SD time-slicing method with representative days correspond to the sample which had the best approximation of the RLDC. The acronyms SD and EI refer to the semi-dynamic and the enhanced integral time-slicing methods, respectively.

yields only limited benefits in approximating the RLDC. As can be observed in Fig. 4.6b, these benefits are predominantly due to a better approximation of variations in the load. Fig. 4.5 further shows that the gain in the accuracy of the RLDC approximation relative to the traditional SD low time-slice division remains almost constant as the wind-energy penetration is increased. This indicates that increasing the resolution in the integral approach brings about no additional benefits related to capturing IRES variability. This can also be observed in Fig. 4.6c. This is due to the fact that the value for wind generation in each time slice is found by taking the average wind generation of all data samples corresponding to this time slice. Due to the higher resolution, the average is taken over a lower number of samples than in the SD low time-slice division. However, already by taking the average value over a small set of dissimilar samples, wind generation is smoothed out. This is in line with the findings in [57].

In contrast, the EI approach drastically improves the approximation of the RLDC, even when only a low number of time slices are used. What is more, the EI approach using only 12 time slices is almost systematically significantly more accurate than the SD approach using 288 time slices. The single exception here is the case where there is no wind power. Whenever a high number of time slices are used in the EI method, both the RLDC, the LDC and the wind generation DC are approximated with a very high accuracy (see Fig. 4.6).

Finally, using a number of representative days (SD repr. days low/high) can yield a similarly high accuracy as the EI approach, provided that a good selection of representative days is made. This can be observed in Fig. 4.5, where the lower end of the whiskers are in the vicinity of the approximation errors obtained by the EI time-slice divisions[4]. However, the large spread in the accuracy obtained using this approach highlights the importance of a good selection of representative days.

Other criteria

As discussed in Section 3.4 of Chapter 3, the RLDC provides valuable information with respect to capturing the impact of intermittent generation on the electrical power system. However, the approximation of the RLDC does not tell the entire story. First, the RLDC does not provide information about the dynamic

[4]It must be noted here that the EI and the SD time-slice division based on representative days can be further improved. For instance, in the EI high case, an equal number of slices were reserved for the load and the wind generation distribution. In addition, the slices were taken such that every load/wind slice represents an equal fraction of the load/wind time series. Moreover, for the time-slice divisions using representative days, we assumed that every day must represent an equal fraction of the entire year. These choices are likely to be sub-optimal.

fluctuations of the residual load. Second, the RLDC does not contain information about the individual elements used to construct this curve, i.e., a temporal representation that results in a good approximation of the RLDC does not necessarily provide a good approximation of the LDC, the wind generation DC or the solar photovoltaic (PV) generation DC. Nevertheless, both these aspects are of importance to assess the value of different technologies in the energy system. Capturing the short-term dynamic fluctuations will determine the arbitrage opportunities, and hence the value of flexibility options, such as storage technologies, flexible power plants, active demand response and increased interconnection capacity. Moreover, an erroneous representation of the wind generation DC or solar PV generation DC can lead to a technology-type bias for two reasons. On the one hand, this can result from an overestimation/underestimation of the yearly generation of wind turbines or solar PV panels. On the other hand, this can also be due to the shape of the wind generation DC or solar PV generation DC. Finally, a technology-type bias can also be introduced whenever the correlation between the different time series is not well approximated. It is therefore important to consider to what extent the different temporal representations capture these aspects.

By definition, the time-slice divisions which determine the values assigned to each time slice by averaging data starting from the entire original time series (i.e., both the SD and the EI method) provide an exact value for the potential annual generation (in terms of TWh) of wind turbines and solar PV panels as well as the annual load[5]. Moreover, by explicitly slicing the resource availability, the shape of the wind turbine generation DC and solar PV generation DC can be approximated with a high accuracy in the EI time-slicing method (as shown in Fig. 4.6c). Finally, also the correlation between different time series is captured well by slicing the joint probability distribution (EI time-slicing method). In contrast, for time-slice divisions relying on a number of representative days, a correct representation of the average value and the distribution of different time series as well as the correlation between different time series cannot be guaranteed. Care is needed in selecting a set of representative days that not only provides a good approximation of the RLDC, but also correctly represents the distributions of the different time series, and the correlation between them. Indeed, even a set of representative days that results in a low error in approximating the RLDC can lead to a significant technology-type bias, and is therefore not applicable. This again stresses the fact that the quality of the SD time-slicing method based on using representative days strongly depends on the choice of the set of representative days.

[5]This is under the assumption that the full time series used as input are wind generation and solar generation time series. Due to the non-linear conversions from wind speed and solar irradiation to electrical power output, this does no longer hold whenever wind speed and solar irradiation time series are used as input.

Regarding the short-term dynamic fluctuations, it is shown that the traditional SD time-slicing methods underestimate the range of IRES generation levels (see Fig. 4.6c). Therefore, despite the fact that these time-slice divisions retain chronology, short-term dynamic variations in the residual load, and hence the value of the different flexibility options, will be significantly underestimated. Increasing the number of time slices in this method yields very limited improvements. In contrast, the EI time-slicing method does capture periods of high and low wind-power generation. However, such a time-slice division does not preserve the chronology, and does therefore not provide information about the frequency of these variations or the time scales at which these variations take place. As a result, time-slice divisions based on the EI method are not suited for assessing the role of time-constrained flexibility options, such as storage technologies and active demand response. Finally, by using representative days, periods of high and low wind-power generation can occur and, within each representative day, the chronology is retained. Consequently, time-slice divisions based on using a number of representative days are likely to be most suited to capture short-term dynamic fluctuations and the value of different flexibility options. It must be noted that the true value of these flexibility options might only become apparent when a high level of technical detail is incorporated. Some of the technical constraints, such as ramping rate restrictions, minimum up and down times and start-up costs, can only be modeled in detail by linking sequential time slices. Therefore, chronological data (at a sufficiently high resolution) is a prerequisite for modeling these constraints. As a result, a model using the EI time-slicing method cannot be extended to incorporate a high level of technical detail, whereas this would be possible for a model relying on representative days.

Finally, when determining which time-slice division to use, also the ease of use can be of importance. In this regard, both the traditional SD method and the EI methods require little effort. In contrast, when using a time-slice division based on a number of representative days, separate algorithms or models need to be deployed to select the representative days, as will be discussed in detail in Section 4.3. As a result, this time-slicing method requires some more effort.

An overview of the advantages and disadvantages of the different time-slicing methods is presented in Tab. 4.2.

4.2.3 Conclusion

Based on the presented analysis, it can be concluded that by a different choice of time-slice division, the way energy-system optimization models represent IRES can be significantly improved without necessitating an increase in the number

	SD	EI	SD repr. days
Approximation RLDC	-	+	(+)
Distribution of different time series	-	+	(+)
Correlation between different time series	-	+	(+)
Short-term dynamics	-	-	(+)
Ease of use	+	+	-

Table 4.2: Overview of the strengths and weaknesses of the different time-slicing methods. The brackets indicate that the result is strongly conditional on the selection of the representative periods.

of time slices. This can be achieved both by time-slice divisions using the EI method and time-slice divisions based on selecting a number of representative historical periods. The main drawback of using the EI time-slicing method is that the chronology is not preserved. Therefore, this method is not directly capable of representing the value of storage and other technologies which can arbitrage over different time steps. In addition, this method might not be capable of reflecting the impact of short-term dynamic variations of the residual load, and the potential/requirement of different flexibility options to deal with these variations. In contrast, using a temporal representation based on using a set of representative historical periods allows retaining chronology (at least within each period), and is therefore better suited to assess the value of different flexibility options. The main drawback of this approach is the difficulty of selecting a good set of representative periods.

Given the potential of the SD method using representative days to provide a good approximation of the RLDC while retaining chronology, the remainder of this chapter will concentrate on this method. More specifically, the focus will shift towards the selection of the representative periods.

4.3 Selecting representative historical periods

4.3.1 Literature review

The literature contains various approaches to select a representative set of historical periods. Nevertheless, frequently a set of representative days (also referred to as typical days or type-days) is used in planning models without documenting how these days are selected, e.g., [135, 136]. In other work, the set of representative days is obtained by using simple heuristics, e.g., [137, 138, 78, 48], sometimes supplemented by randomly selecting some additional days, e.g., [139, 86]. As pointed out by de Sisternes [140], a consistent criterion to select these representative periods or to assess the validity of the approximation is lacking (being the status before our work was reported in the literature). In general, the idea behind most of these simple heuristic approaches is to select a number of periods with different load and/or meteorological conditions in order to capture a variety of different events. As an example, to select three representative days, Belderbos et al. [138] select the day that contains the minimum demand level of the year, the day that contains the maximum demand level and the day that contains the largest demand spread in 24 hours.

More advanced approaches to select a representative set of historical periods can be divided into two groups. The first and by far the largest group employs clustering algorithms to cluster periods with similar load, wind speed and/or solar irradiance patterns into clusters. For every resulting cluster, either the cluster's centroid (i.e., the average of all periods within the cluster) or a single historical period from that cluster is taken as the representative period for that cluster. The weight assigned to each representative period, i.e., the number of times this representative period is assumed to be repeated within a typical year, is proportional to the number of periods that are grouped into its parent cluster. Clustering approaches thus implicitly determine the weight assigned to every selected representative period, which allows appropriately accounting for both common and rare events. This is a major improvement compared to the heuristic approaches discussed earlier. To perform the clustering, different algorithms are employed which can be classified into hierarchical and partitional clustering algorithms. Partitional clustering algorithms directly divide all objects into a predefined number of clusters. In contrast, hierarchical clustering algorithms either start from clusters containing a single object and progressively merge clusters, or start from a single cluster containing all objects and progressively split clusters until the predefined number of clusters is obtained. A more detailed overview of different clustering algorithms is presented in [141]. The goal of all these algorithms is to minimize the sum of the distances between every object (i.e., a period) and the cluster's centroid or median. For the LIMES-EU PSOM, Nahmmacher et al. [142] use Ward's hierarchical clustering algorithm. A similar clustering technique is used in the US-REGEN model to select additional representative periods, after having first used heuristics to select a number of periods containing extreme events [69]. Partitional clustering algorithms, such as so-called k-medoids [141] and k-means [143, 144, 145] are also frequently used. The performance of the k-means, fuzzy C-means and hierarchical Wards clustering algorithm are evaluated in [141], but the differences between these algorithms were found to be minor for the presented case. Besides clustering algorithms, scenario reduction techniques following a similar philosophy as the clustering approaches, such as the fast-backward method, are also employed to select representative periods (see e.g., [131]).

A second group of approaches aims to optimize the selection of representative periods with respect to a predetermined, user-defined criterion (external validity indices). In this approach, the selection procedure is directly based on evaluating the full set of representative periods using external validity indices, whereas in the heuristic and clustering approaches, the selection is based on the characteristics of individual historical periods or the similarity between individual historical periods; this is a clear fundamental distinction. To the best of our knowledge, the only optimization-based approach in the field of energy research is presented by de Sisternes and Webster [140]. In their approach, the set of weeks which best approximates the RLDC is selected by enumerating all possible combinations of a predetermined number of representative weeks. While this approach is shown to achieve good results, it has a number of limitations. First, the number of combinations for selecting k representative periods out of n candidate periods equals $\frac{n!}{k!(n-k)!}$, and thus strongly increases with both the number of candidate periods and the number of periods to select. As a consequence, enumeration is only computationally feasible for selecting up to 5 weeks out of 52. Therefore, using this approach to optimally select a number of representative days instead of weeks is computationally infeasible. Second, the approach does not determine the optimal weights for each selected period. Finally, the approximation of the RLDC is used as a decision criterion, but the RLDC is dependent on the investments in IRES. Therefore, the approach cannot be used for models with endogenous investments in IRES.

Although multiple approaches for selecting representative periods are available from the literature, there is no consistent comparison of the quality of these different approaches. In this regard, the current literature is restricted to comparing different clustering algorithms. More complete information on the quality of different approaches is vital for ESOMs and PSOMs as a better selection of a representative set of historical periods allows improving the accuracy of these models without increasing computational complexity. Moreover, despite the multitude of different approaches to select representative periods, there is not a single optimization-based approach in the field of energy research that can be used to select a sufficiently high number of representative periods. It is our aim to provide a suitable optimization-based approach.

The objective of the remainder of Section 4.3 is to develop a sound approach for selecting representative historical periods. To this end, (i) criteria and metrics for representativeness are proposed, (ii) a novel optimization-based approach is presented and (iii) this approach is compared to different approaches available in the literature in terms of both accuracy and ease of use.[6]

4.3.2 Methodology

Temporal aspects and metrics for evaluation

To effectively quantify the accuracy of using a set of representative periods, appropriate metrics must be defined. A first option is to define metrics based on the accuracy with which the results (e.g., the projected system costs, or the capacity mix) generated by ESOMs/PSOMs using a set of representative periods are approximated. A second option is to define certain temporal aspects which drive the results of ESOMs/PSOMs, and to define metrics to quantify the accuracy of approximating these temporal aspects. In this work, the latter option is adopted. The advantage of this approach is that the results are independent from the assumptions which need to be taken in the ESOM/PSOM used to evaluate the set of representative days (e.g., assumed investment costs and fuel prices).

From the literature [69, 142, 146], we synthesize and borrow the following list of temporal aspects that impact the results of ESOMs/PSOMs:

1. the annual load and average IRES capacity factors;
2. the distribution of values for each time series
3. the correlation between the different time series;
4. the variability of each time series.

First, the selected set of periods should preserve the annual electricity demand and the average IRES capacity factors for each model region. To evaluate the quality of the approximation in this respect, the average value (over all considered time series $p \in \mathcal{P}$) of the relative errors in approximating the average value of each time series is used as a metric; see Eq. (4.1).

$$REE_{av} = \frac{\sum\limits_{p \in \mathcal{P}} \left(\left| \frac{\sum\limits_{t \in \mathcal{T}} DC_{p,t} - \sum\limits_{t \in \mathcal{T}} \widetilde{DC}_{p,t}}{\sum\limits_{t \in \mathcal{T}} DC_{p,t}} \right| \right)}{\|\mathcal{P}\|} \tag{4.1}$$

[6]Ease of use comprises the required effort for implementing the approach, the computational cost of executing the approach as well as the flexibility to incorporate user-specific constraints.

Since for the case presented here, the relative error in the average value of a time series is identical to the relative error of the energy content of a time series, we refer to this metric as the relative energy error (REE_{av}) in the remainder of this text. Note that we use $|.|$ to refer to the absolute value, while $\|.\|$ is used to refer to the cardinality of a set, i.e., the number of elements contained within the set.

Second, a more stringent requirement is that the distribution of load and IRES generation levels, and their respective frequency of occurrence correspond to the one observed in the entire time series. Regarding the time series for IRES generation, it is crucial to account for both periods of very high IRES generation, during which partial curtailment might be required, and periods of near-zero IRES generation, which determine the need for back-up capacity. Moreover, capturing the distribution of IRES generation is required to account for the reduction in operating hours of different types of dispatchable power plants. Thus, by capturing the distribution of each time series, major challenges related to the integration of IRES are accounted for. Therefore, this criterion, which has also been used in [142, 144], is considered to be the most important criterion for evaluating a set of representative periods. The information regarding the distribution of values and their respective frequency of occurrence can be represented by the DC of the time series. Hence, the average normalized root-mean-square error (NRMSE) of the approximation of the DC of each time series is used as a second metric, to which we refer as $NRMSE_{av}^{DC}$ (Eq. (4.2)).

$$NRMSE_{av} = \frac{\sum\limits_{p \in \mathcal{P}} \left(\frac{\sqrt{\frac{1}{\|\mathcal{T}\|} \cdot \sum\limits_{t \in \mathcal{T}} (DC_{p,t} - \widetilde{DC}_{p,t})^2}}{\max(DC_p) - \min(DC_p)} \right)}{\|\mathcal{P}\|} \tag{4.2}$$

The *approximation* of the DC, $\widetilde{DC}_p$, can be constructed by sorting the data of the selected periods from high to low while correcting for the fraction of a year that each selected period represents. Below, the index $t \in \mathcal{T}$ is used to refer to a specific time step of the sorted original time series (e.g., quarter-hourly or hourly interval).

Third, the correlation between different time series can impact results. Within a single region, this correlation (e.g., between the load and solar PV generation) influences the RLDC, and therefore the expected number of operating hours of different thermal generation technologies. In addition, it impacts the need for curtailment of IRES, as well as their market value [147]. Moreover, the correlation between different regions is important to account for geographical smoothing effects of the load, solar PV generation, and particularly wind generation, and the corresponding value of transmission grids [146]. As a metric to quantify whether the actual correlation is captured by the selected representative periods, the average absolute difference between the correlation based on the data of the entire time series, and the correlation based on the data in the selected representative periods is used. This is referred to as the average correlation error (CE_{av}) in the remainder of this text (Eq. (4.3)).

$$CE_{av} = \frac{2}{\|\mathcal{P}\| \cdot (\|\mathcal{P}\| - 1)} \cdot \Big(\sum_{p_i \in \mathcal{P}} \sum_{p_j \in \mathcal{P}, j > i} \big| corr_{p_i,p_j} - \widetilde{corr}_{p_i,p_j} \big| \Big) \tag{4.3}$$

The Pearson correlation coefficient is used to quantify the correlation $corr_{p_1,p_2}$ between two time series $p_1, p_2 \in \mathcal{P}$ (Eq. (4.4)).

$$corr_{p_1,p_2} = \frac{\sum\limits_{t \in \mathcal{T}} \big((V_{p_1,t} - \overline{V}_{p_1}) \cdot (V_{p_2,t} - \overline{V}_{p_2}) \big)}{\sqrt{\sum\limits_{t \in \mathcal{T}} (V_{p_1,t} - \overline{V}_{p_1})^2 \cdot \sum\limits_{t \in \mathcal{T}} (V_{p_2,t} - \overline{V}_{p_2})^2}}. \tag{4.4}$$

Here, $V_{p1,t}$ represents the value of time series p_1 in time step t. Moreover, $\overline{V}_{p_1}$ and $\overline{V}_{p_2}$ indicate the mean value of time series p_1 and p_2 respectively. As the Pearson correlation coefficient has a value of 1 in case of total positive correlation, a value of 0 in case of no correlation and a value of -1 in case of total negative correlation, the values for CE_{av} lie in the range [0,2].

Fourth, the dynamics of fluctuating load and IRES generation time series can impact results. Short-term fluctuations, on time scales of minutes up to hours, are important to account for the limited flexibility of dispatchable power plants (e.g., maximum ramp rates, minimum up and down times), as well as the potential of storage technologies. To quantify to what extent the distribution of short-term fluctuations is captured, we introduce the concept of a ramp duration curve (RDC). The RDC for each time series is found by differentiating and subsequently sorting the original time series. The RDC then represents the distribution of the deviations between the values of a time series between adjacent time steps. Accordingly, the metric used is the average NRMSE of the approximation of the RDC ($NRMSE_{av}^{RDC}$):

$$NRMSE_{av}^{RDC} = \frac{\sum\limits_{p \in \mathcal{P}} \left(\frac{\sqrt{\frac{1}{\|\mathcal{T}\|} \cdot \sum\limits_{t \in \mathcal{T}} (RDC_{p,t} - \widetilde{RDC}_{p,t})^2}}{\max(RDC_p) - \min(RDC_p)} \right)}{\|\mathcal{P}\|} \tag{4.5}$$

Medium-term fluctuations, comprising weekly and seasonal fluctuations, are important to account for the limited energy storage capacities of different storage technologies. For example, longer periods of low wind speeds and solar irradiance, during which stored energy might be exhausted, can determine the need for firm back-up capacity. To what extent medium-term fluctuations are captured depends mainly on the input parameters used for selecting representative periods, rather than the used approach in itself. These input parameters are closely related to the temporal structure of the ESOM/PSOM. Examples of such input parameters include the time interval to which the approach for selecting representative periods is applied (e.g., representative periods can be selected for each month, season or year) and the choice of the duration of each individual selected period (e.g., representative hours, days or weeks). As the focus in this section is on approaches to select representative periods rather than the temporal structure of ESOMs/PSOMs, no metric is introduced for capturing medium-term dynamics. However, metrics for capturing medium-term dynamics could be included.

Methods for selecting representative periods

Different approaches to select representative periods are evaluated by comparing all four metrics presented above. The results of this evaluation will be shown for the selection of an increasing number of representative days (N_{repr}). The following approaches to select representative periods are evaluated:

1. Heuristics (H);
2. Ward's hierarchical clustering algorithm (CA);
3. Random selection (RS);
4. MILP optimization model (OPT);
5. Hybrid approach: random selection followed by optimal weighting (HYB).

The simple heuristics (H) employed in this work are presented in Tab. 4.3. The total number of days selected is presented in the utmost left column. These days are obtained by selecting for every period (indicated in the second column), the days corresponding to the criteria presented in the third to fifth column.

The clustering algorithm used is Ward's hierarchical clustering algorithm. This algorithm starts from a single cluster for each day. For each possible merge of two clusters, the algorithm then determines the merged cluster's centroid by taking the average value over all days in the merged cluster for each time step and time series. Next, for the clusters remaining after each possible merge of two clusters, the overal sum of the squared deviations between the data corresponding to the days within the resulting clusters and the clusters's centroids is calculated. The merge of two clusters which minimizes this metric is then selected and the

N_{repr}	Period	Load	Wind	PV
2	Year	Highest peak, lowest valley	-	-
4	Year	Highest peak, lowest valley	Highest and lowest avg. generation	-
8	Summer, Winter	Highest peak, lowest valley	Highest and lowest avg. generation	-
12	Summer, Winter, Intermediate	Highest peak, lowest valley	Highest and lowest avg. generation	-
24	Spring, Summer, Fall, Winter	Highest peak, lowest valley	Highest and lowest avg. generation	Highest and lowest avg. generation

Table 4.3: Overview of the simple heuristic used to select a number of representative days. For each period indicated in the column 'Period', days are selected depending on the load, wind and solar generation within the days corresponding to the period. The criteria used for selection are indicated in the columns 'Load', 'Wind' and 'PV'. The total number of selected days is indicated by N_{repr}.

two clusters are merged. This process is repeated until the predefined amount of clusters remain. For each remaining cluster, the day closest to the cluster's centroid forms the selected representative day. For a mathematical description of the algorithm, we refer to [142].

The third approach is to repeatedly select a random subset of days (RS), and retain from all these subsets the subset which obtained the lowest errors. This approach is closely related to the enumerative approach used to select a set of representative weeks proposed in [140]. However, calculating the error metrics for all possible subsets of days from a single year is computationally infeasible if the cardinality of the subset exceeds 3. Therefore, the number of randomly selected subsets of days is restricted to 50,000.

The fourth approach (OPT) is a newly developed approach that employs a MILP optimization model to identify which days are selected (binary variables) as well as the weight assigned to each day (continuous variables). The model formulation is presented in Section 4.3.3.

Finally, another new and novel, hybrid, approach (HYB) that combines features of the RS and the OPT approach is developed here in this work. In this approach, a number of random subsets of days are taken and for each subset, the weight given to each day is optimized. The set of weighted days that achieves the lowest errors is retained. Again, 50,000 randomly selected subsets are taken.

Data and assumptions

The original time series used include a time series for the electricity demand, a time series for onshore wind generation and a time series for solar PV generation. All data correspond to the Belgian electricity system in the year 2014 and the time series have a 15-minute resolution [134]. As one cannot simply assume that the year 2014 is a representative year for the different time series, it is advised to use multiple years of data to construct the different DCs. However, as the goal in this work is to analyze to what extent the different approaches are capable of selecting representative periods to approximate a given original time series, it is reasonable to assume that the size of the original time series will not significantly influence the presented results.

The discussion in this work is restricted to selecting days as representative periods as days are more frequently applied than e.g., hours or weeks.

4.3.3 Optimization model formulation

Basic model

As discussed in Section 4.3.2, primarily, the set of representative days should accurately represent the DC of each time series. An optimization model should therefore be capable of selecting a set of representative days (and associated weights), construct the approximation of the DC based on the selected days and corresponding weights, and calculate a metric for the approximation error that can be minimized. Note that the number of steps of the approximated DC depends on the number of days selected and the resolution of the data of each day. For example, the approximated DC displayed in Fig. 4.7 is constructed by selecting 2 representative days with a 2-hourly resolution, resulting in a total of 24 steps. However, obtaining the approximation of the DC requires sorting the values of the selected days which is difficult to integrate in a single optimization framework.

Nevertheless, it is possible to get a clear view on what the approximated DC looks like which does not require sorting the data of the selected days. To this

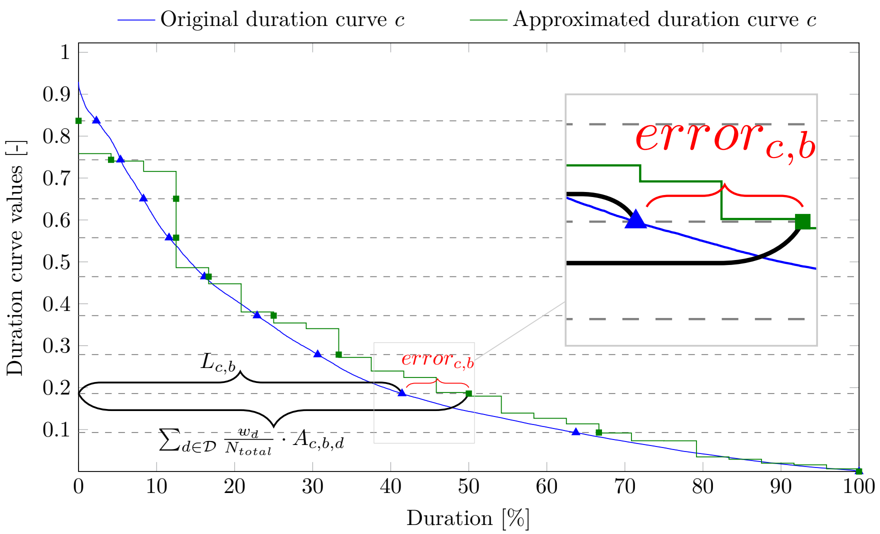


Figure 4.7: Visualization of the error term $error_{c,b}$. The duration curve is divided into 10 bins. The error at the bottom of the bin is displayed for bin $b = 8$.

end, each DC $c \in \mathcal{C}$ is divided into a number of bins $b \in \mathcal{B}$, as visualized by the dashed lines in Fig. 4.7. Each bin thus corresponds to values within a specific range (the highest values belong to the first bin, the lowest values correspond to the last bin). As the original time series is known, the share of time during which this time series has a value greater than or equal to the lowest value in the range corresponding to bin b is known (marked by a $\blacktriangle$ in Fig. 4.7). For a DC $c \in \mathcal{C}$, this value is represented by the parameter $L_{c,b}$. Similarly, for every potential representative day $d \in \mathcal{D}$, the share of time in day d during which the time series exceeds the lowest value of the range corresponding to a bin b is known. This information is represented by the parameter $A_{c,b,d}$. A graphical representation of this parameter for Belgian load data of 2014 and a number of bins equal to 10 is shown in Fig. 4.8. This figure shows that, as can be expected, in every day, the load levels exceed the lowest value of the range corresponding to the last bin in 100% of the time. In contrast, only during a small fraction of the time of some winter days, electricity load values exceed the lower value corresponding to the first bin. This figure also clearly illustrates seasonal and weekly trends.

Assuming that a subset of representative days $\mathcal{D}' \subset \mathcal{D}$ is selected and a weight w_d is assigned to each selected representative day $d \in \mathcal{D}'$, the share of the

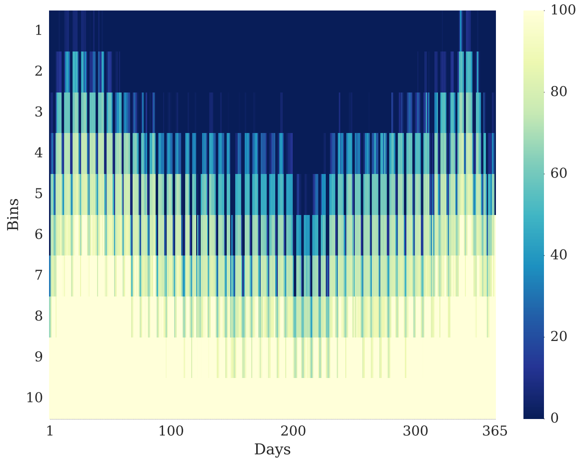


Figure 4.8: Graphical representation of the parameter A (representing how different days contribute to the overall distribution of the time series) for the Belgian load during all days of 2014 and a number of bins equal to 10. The color scales indicate the share of time of each day during which the lowest value of the range corresponding to the different bins is exceeded.

time during which the approximated DC has a value greater than or equal to the lowest value in the range corresponding to bin b is also known, i.e., $\sum_{d \in \mathcal{D}'} \frac{w_d}{N_{total}} \cdot A_{c,b,d}$ (indicated by a ■ in Fig. 4.7). Here, N_{total} reflects the total number of times a single representative period has to be repeated to scale up to an entire year, e.g., N_{total} equals 365 in case representative days are selected and 52 in case representative weeks are selected). Now, if the weight w_d assigned to a day $d \in \mathcal{D}$ can only be non-zero if the day is selected (i.e., $d \in \mathcal{D}'$), the expression can be replaced by $\sum_{d \in \mathcal{D}} \frac{w_d}{N_{total}} \cdot A_{c,b,d}$.

The difference between the original and the approximated DC in the share of the time that the lowest value in the range corresponding to bin b is exceeded is taken as an error metric ($error_{c,b}$). This error term is defined in Eq. (4.7) and visualized in Fig. 4.7. Hence, by classifying the data points (e.g., quarter-hourly or hourly values) of all potential representative days into a number of bins, the need to sort the data of the selected days within the optimization in order to obtain a measure for the quality of the approximation is eliminated. The optimization model minimizes the sum of the errors terms, for all considered DCs $c \in \mathcal{C}$ and bins $b \in \mathcal{B}$ by selecting a single set of representative days and corresponding weights, as shown in Eq. (4.6):

$$\min_{u_d, w_d} \left(\sum_{c \in \mathcal{C}} \sum_{b \in \mathcal{B}} error_{c,b}\right), \tag{4.6}$$

subject to:

$$error_{c,b} = |L_{c,b} - \sum_{d \in \mathcal{D}} \frac{w_d}{N_{total}} \cdot A_{c,b,d}|, \, \forall c \in \mathcal{C}, b \in \mathcal{B}, \tag{4.7}$$

$$\sum_{d \in \mathcal{D}} u_d = N_{repr}, \tag{4.8}$$

$$w_d \leq u_d \cdot N_{total}, \quad \forall d \in \mathcal{D}, \tag{4.9}$$

$$\sum_{d \in \mathcal{D}} w_d = N_{total}, \tag{4.10}$$

$$u_d \in \{0, 1\}, \; \forall d \in \mathcal{D}; \quad w_d \in \mathbb{R}_0^+, \; \forall d \in \mathcal{D}. \tag{4.11}$$

Equation (4.8) imposes that the number of selected periods corresponds to the predefined number of representative periods N_{repr}. Equation (4.9) restricts non-zero weights to selected periods, by using a binary variable u_d which indicates whether day d is selected or not. Moreover, the maximum weight that can be assigned to a single selected period is restricted to the number of repetitions required to scale the duration of a single representative period to one year (N_{total}). The weight from all selected periods can therefore be chosen freely, which is important to efficiently account for both common and rare events. Finally, Eq. (4.10) guarantees that the total duration of the weighted set of representative periods corresponds to one year.

Note that in the HYB approach, the variables u_d are fixed in correspondence to the randomly selected subset, such that only the weights w_d are optimized.

Extended model

To explicitly account for short-term dynamic aspects in the optimization, the ramp duration curve (RDC) of each time series can be constructed and appended to the set of DCs $c \in \mathcal{C}$ that need to be approximated. Thus, the model formulation (Eq. (4.6)-(4.11)) remains unchanged. The only difference with the basic model is that the set $\mathcal{C}$ not only comprises the DC of each time series, but also the RDC of each time series.

To account for medium-term fluctuations (e.g., seasonal fluctuations), the original time series can be split up into a number of medium-term periods

$m \in \mathcal{M}$, where each medium-term period has its own DC. A first option is to select a number $N_{repr,m}$ of representative periods $d \in \mathcal{D}_m$ for each medium-term period individually. Correspondingly, the total weights of the days representative for this medium-term period equals $N_{total,m}$. Thus, the optimization (Eq. (4.6)-(4.11)) would have to be repeated $\|\mathcal{M}\|$ times. An alternative approach would be to add additional constraints to the optimization problem to restrict the approximation error in each medium-term period $m \in \mathcal{M}$.

Up to now, the model does not account for the correlation between different time series. It is important to note from the definition of the sample correlation $corr_{p_1,p_2}$ (Eq. (4.4)) that both factors in the denominator of the definition of the sample correlation are already approximated implicitly by approximating the DC of time series p_1 and p_2 (as done by the basic model). That is, a set of representative periods which result in a good approximation of the DC of a time series p_1, will also provide a good approximation of $\sum_{t \in \mathcal{T}}(V_{p_1,t} - \overline{V}_{p_1,t})$. However, this does not hold for the numerator of Eq. (4.4). Therefore, an additional time series $(V_{p_1,t} - \overline{V}_{p_1,t}) \cdot (V_{p_2,t} - \overline{V}_{p_2,t})$ is created. Positive values of this time series correspond to times with a positive correlation, i.e., both $V_{p_1,t}$ and $V_{p_2,t}$ are either above or below their average value, whereas negative values correspond to times with a negative correlation. Again, a DC of this time series can be constructed, and added to the set of DCs that need to be approximated. The model will then select a set of representative days to not only account for the distribution of each DC, but also to approximate the DC of this "correlation DC".

Fig. 4.9 presents a schematic of the different steps involved in the presented approach.

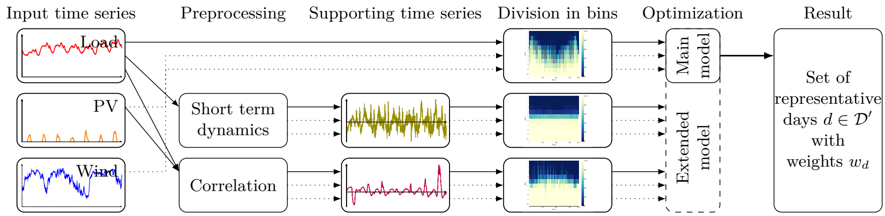


Figure 4.9: Schematic of the different steps of the OPT approach.

Unless specifically stated, the results of the OPT and HYB approach, to be presented in Section 4.3.4, correspond to the basic model, i.e., without extending the model with additional RDCs or time series to improve approximating the correlation.

It must furthermore be noted that the presented method can be easily adapted to include different or additional time series for which it is relevant to approximate the variability. For instance, in ESOMs, the variable demand for space heating could be represented by including a time series indicating the demand for space heating (or related time series such as the outside air temperature). Another example could be to model active demand response from electrical heating systems or electric vehicles by adding time series to indicate the instantaneous potential for demand response which could for example be dependent on the outside air temperature, the day of the week and the time of the day.

4.3.4 Results and discussion

Time series approximation

The results for all five approaches discussed in Section 4.3.2 are presented in Fig. 4.10-4.13 and Fig. 4.15 for the different error metrics. For the approaches based on randomly selecting subsets of representative days (RS and HYB), the distribution of the results of the 50,000 subsets is presented. The box visualizes the median value as well as the 25^{th} and 75^{th} percentiles, whereas the whiskers correspond to the highest and lowest values obtained. For the OPT and HYB approach, a number of bins $\|\mathcal{B}\|$ equal to 40 is used for every DC. Every bin is constructed such that the range of values for each bin is identical. All OPT runs are performed with an optimality gap of 1%, and a maximum solver time of 6 hours. All runs are performed on an Intel®Core™Quad CPU Q9550 @ 2.83GHz×4, with a memory of 13.5GiB, and a 64-bit system.

As discussed in Section 4.3.2, the set of representative days should primarily provide a good approximation of the DC of each time series. The $NRMSE_{av}^{DC}$ obtained using the different approaches is presented in Fig. 4.10. As can be seen, the OPT approach obtains the lowest error for all number of days considered. The approximation of the different DCs using the OPT approach to select a varying number of representative days is shown in Fig. 4.11. The errors obtained using the hybrid approach are only slightly higher (except for selecting 2 representative days, where an identical solution is found). More surprisingly, the errors obtained by approach RS are systematically lower than those obtained using the clustering algorithm (CA) even though all days in the RS approach are assigned equal weights[7]. Finally, the errors obtained using the heuristics are high. For all but for two days, more than 75% of the randomly selected sets of days obtains lower errors than those obtained using the heuristics. This is

[7] Recall that the solution of the random selection approach is the best sample from the presented distribution.

due to the fact that the heuristics aim to account for different types of events, but do not account for their frequency of occurrence.

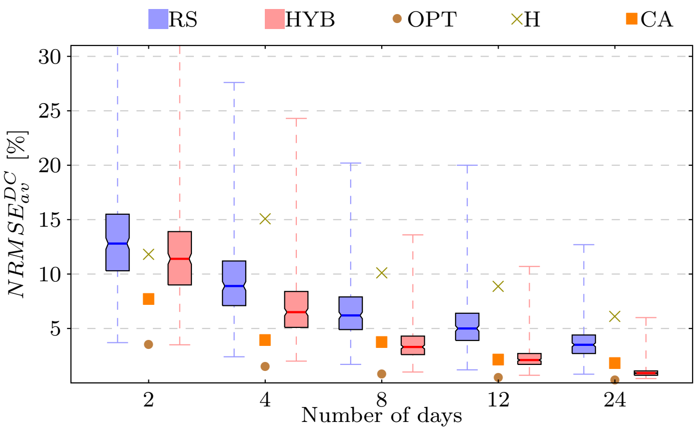
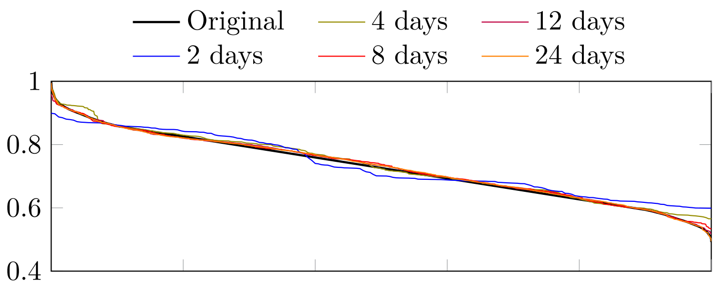


Figure 4.10: Error in approximating the duration curves (DCs).

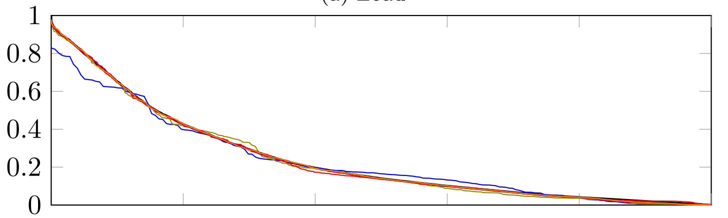
These results imply that by using a better approach to select a set of representative days, the accuracy of planning models can be improved significantly without increasing the number of time segments (and therefore the computational cost). Seen from a different perspective, this also means that the number of days can be reduced while maintaining a similar accuracy. This can be seen very clearly in Fig. 4.10, where the OPT and HYB approach using 2 days obtain a similar accuracy as the CA selecting 8 days. Similarly, the approximation obtained by selecting 4 days using the OPT approach has a similar accuracy as the approximation obtained using the CA selecting 24 days.

Fig. 4.12 displays the REE_{av} for all approaches. For all but the heuristic approach, the average relative energy error is well below 5%. The fact that the heuristics do not properly account for the frequency of occurrence of different events is reflected in the high values for the REE_{av}. As discussed in Section 4.3.2, approximating the DC of a time series is a more stringent requirement than approximating its average value or energy content. Therefore, sets of days with a low $NRMSE_{av}^{DC}$ also have a low REE_{av}. This can be seen in the inner box plots for the RS and HYB approach, which show the distribution of the REE_{av} for the 1% subsets of days that obtained the lowest $NRMSE_{av}^{DC}$. Fig. 4.12 displays furthermore that for the RS, OPT and HYB approach, the REE_{av} is very small. Therefore, the differences between these approaches are of less importance, e.g., for 12 days, the REE_{av} equals 0.21%, 0.12% and 0.01% in the RS, OPT and HYB approach respectively.

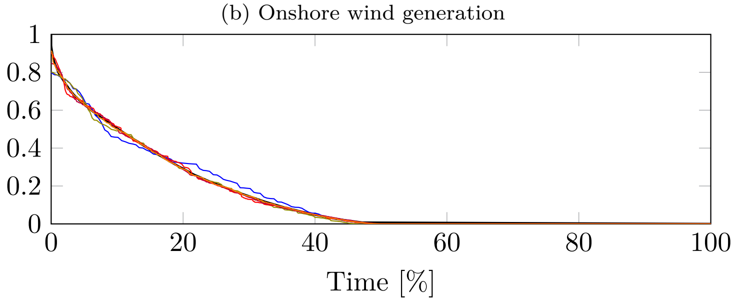
The error in approximating the correlation between the different time series



(a) Load



(b) Onshore wind generation



(c) Solar PV generation

Figure 4.11: Approximation of the duration curves (DCs) using the OPT approach to select a varying number of representative days

is shown in Fig. 4.13. The CE_{av} tends to decline with an increasing number of days. Again, the range of the CE_{av} is high for randomly selected days. However, differently from the REE_{av}, a low $NRMSE_{av}^{DC}$ does not guarantee a low CE_{av}. This can be seen in the inner box plots which show the distribution of the CE_{av} for the 1% subsets of days that obtained the lowest $NRMSE_{av}^{DC}$. As a consequence, if the correlation is not explicitly accounted for in the OPT and HYB approaches, the CE_{av} for these approaches can be relatively high. As discussed in Section 4.3.3, the correlation can be accounted for in the OPT approach by approximating an additional DC for every pair of time series for

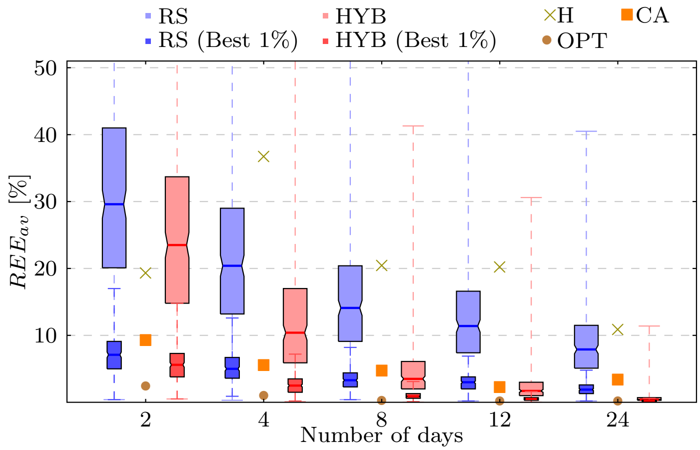


Figure 4.12: Average error in approximating the average value of the different time series.

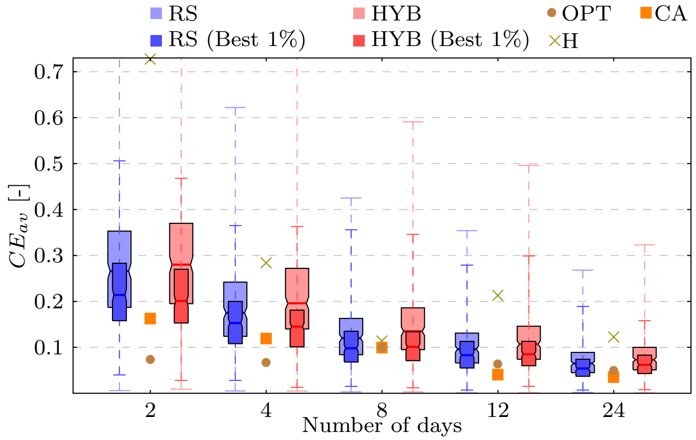


Figure 4.13: Error in approximating the correlation between the different time series.

which the correlation is important to capture. However, this will lead to a trade-off between the $NRMSE_{av}^{DC}$ and the CE_{av}, as is shown in Fig. 4.14. This figure illustrates that the CE_{av} obtained with the OPT approach can be greatly reduced with only a minor increase in the $NRMSE_{av}^{DC}$. In contrast, the CA groups together days with similar conditions for all time series and therefore already implicitly accounts to some extent for the correlation between the considered time series. This is reflected in the results shown in Fig. 4.13

where the CE_{av} for the clustering approach is consistently relatively low.

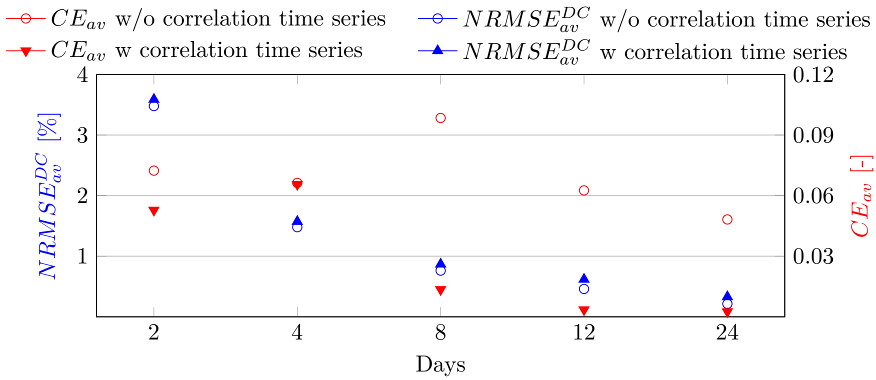


Figure 4.14: Impact of including the correlation time series in the OPT approach.

The errors for approximating the RDCs for all approaches are presented in Fig. 4.15. A first thing that can be noted is that these errors are significantly lower than for the approximation of the DCs. Moreover, only a moderate decrease of this error with the number of representative days can be observed. Similarly to the CE_{av}, a good approximation of the DCs (low $NRMSE_{av}^{DC}$) does not imply a good approximation of the RDCs (low $NRMSE_{av}^{RDC}$). Nevertheless, there is some correspondence between the $NRMSE_{av}^{DC}$ and the $NRMSE_{av}^{RDC}$. This is because the probability distribution of the ramp of a time series is dependent on the actual value of this time series (e.g., at periods of very high load, it is unlikely that the load will further increase). As a result, sets of days which approximate the DC of each time series with a high accuracy, have a higher probability of capturing the distribution of ramps. To improve capturing the distribution of ramps in the OPT approach, the RDCs can be added to the optimization, as discussed in Section 4.3.3. This would again lead to a trade-off between approximating the DCs and the RDCs. Following the same reasoning as for the CE_{av}, the clustering approach already implicitly accounts for some dynamics of the considered time series.

Ease of use

Reducing the errors in capturing different temporal aspects for a given number of representative periods is particularly important for applications with a high computational cost. For these applications, the OPT and HYB approaches are shown to achieve the best results, closely followed by the RS approach. However, for applications where the computational cost of solving the ESOM/PSOM is less stringent, other aspects, such as the effort required for implementing, the

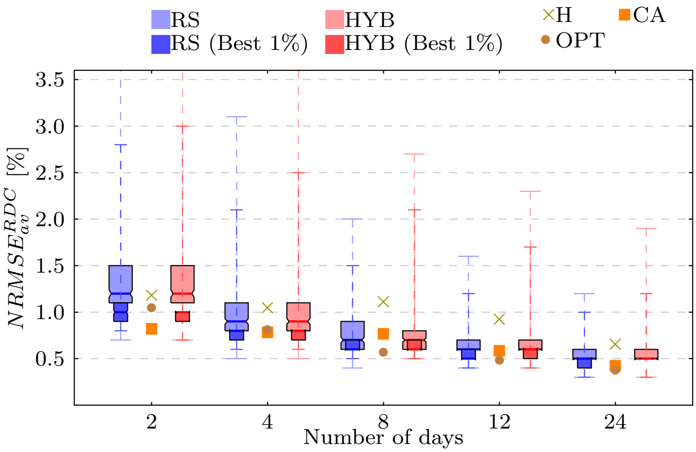


Figure 4.15: Error in approximating the ramp duration curves (RDCs).

computational cost of executing and the flexibility of the approach for selecting representative historical periods can be decisive for the approach to use.

In terms of the implementation effort, the H and RS approaches require the lowest effort, while the CA, OPT and HYB approaches all require a more significant implementation effort. In addition, the OPT approach requires the availability of solvers for MILP problems. In a project funded by the Energy Technology Systems Analysis Program[8] (ETSAP), the OPT approach has been fine-tuned for direct application in combination with the TIMES model generator. The model, implemented in GAMS and Microsoft Excel, including a user manual, is free to download from following site: `https://iea-etsap.org/index.php/etsap-projects`. In this regard, the implementation effort of the OPT approach is eliminated.

The computational resources required to solve the MILP problem used in the OPT approach are high. As mentioned in Section 4.3.2, a relative optimality gap of 1% is applied but the solver is stopped if no solution satisfying this criterion is found within 6 hours. For all instances except for the case where only 2 representative days were selected, the solver timed out after 6 hours[9]. In contrast, the clustering approach using Ward's hierarchical clustering algorithm can be solved within a few minutes. Finally, both the RS and HYB approach face a high computational cost. Despite the fact that the HYB approach requires solving an

[8]ETSAP is an implementing agreement of the International Energy Agency. More information can be found on following website: `http://www.iea-etsap.org/web/index.asp`.

[9]After 6 hours, the optimality gap for the run selecting 4 days remained to be 86%. When more days were selected, the optimality gap increased to over 99%.

additional linear programming (LP) model for every randomly selected subset of days, the computational cost of the RS and HYB approach is similar (as long as the same amount of randomly selected subsets of days are used in both approaches). More specifically, the computation time is on average 1.27 seconds and 1.75 seconds for a single randomly selected set of days in the RS and HYB approach respectively[10]. The total computation time scales linearly with the number of randomly selected samples. The difference in time between the RS and the HYB approach corresponds to the time needed to optimize the weights. Hence, the time required to calculate the error metrics for every subset of days dominates the calculation time. Calculating the error metrics for the 50,000 subsets of days is computationally demanding.

A trade-off between the accuracy of the solution and the number of evaluated subsets of days can be made. This trade-off is visualized in Fig. 4.16, which again shows the approximation error of the DCs for the different approaches. Suppose only 100 randomly selected subsets of days are used in the RS and HYB approach, the resulting $NRMSE_{av}^{DC}$ (i.e., the lowest $NRMSE_{av}^{DC}$ of these 100 subsets) depends on which 100 subsets are taken. By repeatedly taking 100 random subsets, the distribution of the error obtained for the best subset can be constructed. This cumulative distribution is shown in Fig. 4.16 for both the RS and HYB approach and both for the case where 100 and 10,000 subsets would be used. A first thing to observe is that, even if the number of subsets is reduced to 10,000 in the RS approach, the accuracy of this approach is higher than for the CA approach with a very high probability. For the HYB approach, this remains valid even if the number of subsets would be reduced to 100. Another interesting observation is that, for a low number of days, it is mainly the number of subsets that determines the accuracy of the result. However, as the number of days increases, the value of using a high number of subsets decreases (i.e., the difference between the full and dotted lines decreases). In contrast, the value of optimizing the weights of the randomly selected days (i.e., the difference between the blue and red curves) is relatively low if a low number of days is selected, but increases with the number of representative days. To conclude, the number of subsets of days, and thus the execution cost, can be significantly reduced without a big loss in accuracy if a high number of representative days needs to be selected, and more so in the HYB approach than in the RS approach.

The value of having an approach to more accurately select a set of representative periods depends on the computational restrictions of the ESOM/PSOM. In case there is a hard limit on the computational cost, and hence, on the number of

[10] For the results presented here, the implementation of the RS and HYB approach has been done in python 2.7.11. More advanced programming languages, specified to do bulk computations on large datasets including sorting algorithms, can lower the computation time.

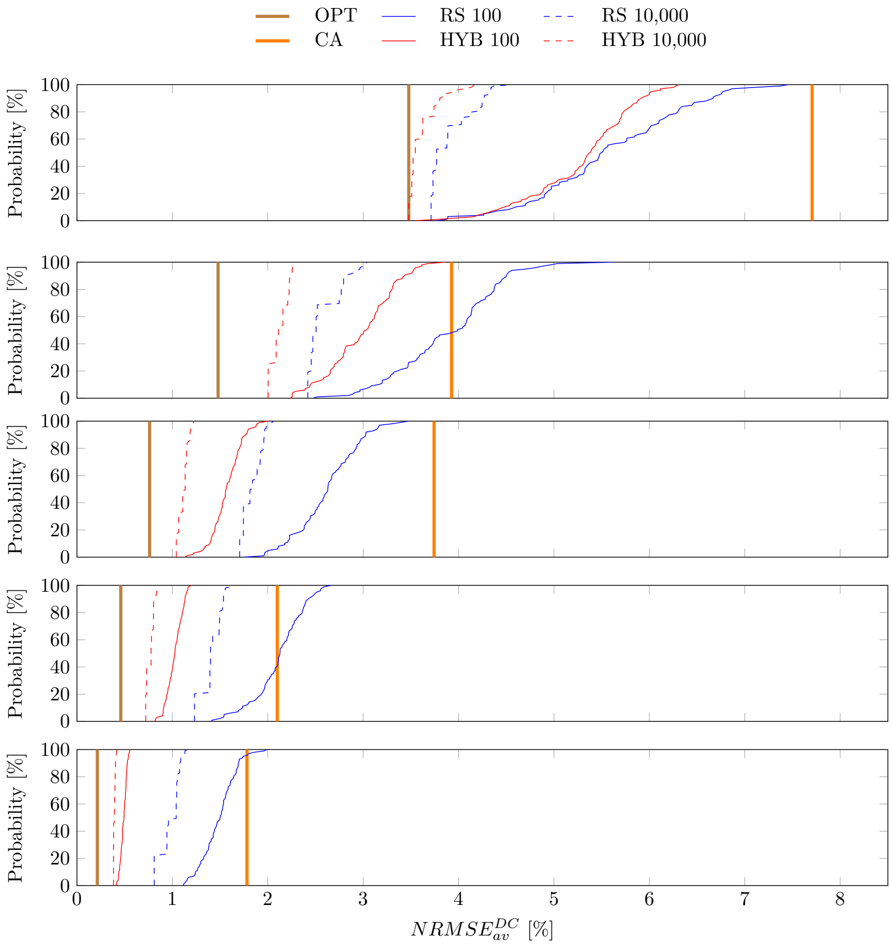


Figure 4.16: Error in approximating the duration curves (DCs). The five panels refer from top to bottom to the results for 2, 4, 8, 12 and 24 representative days.

representative periods that can be used, the OPT approach allows improving the accuracy of the ESOM/PSOM. In other cases, the presented approach allows reducing the computational cost of the ESOM/PSOM by using a smaller number of better selected representative days while achieving the same quality of model outcome in terms of accuracy and representation of power system characteristics. In these cases, it is up to the user to make the trade-off between spending additional computational resources on the approach to select representative periods, or on the ESOM/PSOM. However, it is important to realize that ESOMs/PSOMs are typically used for scenario analysis (and additional sensitivity analyses). As a result, the ESOM/PSOM needs to be solved numerous times. In contrast, the approach to select a representative set of historical periods has to be executed only once.

Finally, the flexibility to use the approach for different applications is important. A frequently encountered case where the flexibility of the approach is valuable is if the user wants to force certain days into the solution (e.g., the day containing the yearly peak in electricity demand). An efficient implementation of this additional constraint of the problem is straightforward in the RS, OPT and HYB approach, but less so in the CA approach.

To summarize, a qualitative overview of the discussed strengths and weaknesses of the different approaches is presented in Tab. 4.4.

Criterion	H	CA	RS	OPT	HYB
Accuracy	- -	+-	+	++	++
Implementation cost	++	-	++	- -	- -
Execution cost	++	+	- -	-	-
Flexibility	-	-	+	++	++

Table 4.4: Qualitative strengths and weaknesses of the considered approaches for selecting representative days. H, CA, RS, OPT and HYB refer to the approaches based on simple heuristics, a clustering algorithm, evaluation of a large number of randomly selected days, the developed optimization model and a hybrid approach between the random selection and optimization approach, respectively.

Impact of the temporal resolution

Up to now, all results were based on selecting a varying number of representative days, all having the original 15-minute resolution. Every representative day is therefore represented by 96 time slices. This implies that, given a restriction for the total number of time slices, more representative days could be selected if the resolution would be lowered. As the goal is to make optimal use of the available number of time slices, the trade-off between the number of representative days and the temporal resolution will now be analyzed[11].

[11] In terms of the optimization procedure, using a different temporal resolution for the representative days only impacts the input parameter $A_{c,b,d}$

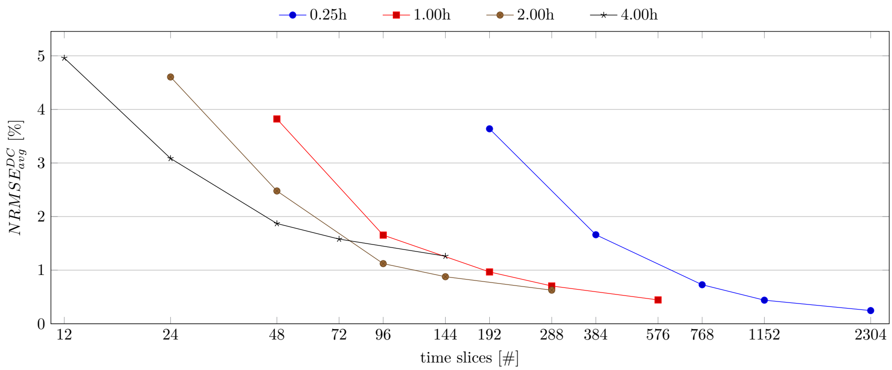


Figure 4.17: Average normalized root-mean-square error (NRMSE) of the approximation of the duration curves of the original time series for an increasing number of time slices. For each resolution, a varying number of representative days are selected, yielding a total number of time slices. A trade-off between the number of representative days and the resolution of the selected days can be observed.

Fig. 4.17 presents the average NRMSE of the approximation of the DCs of the original time series (with a 15-minute resolution) as a function of the total number of time slices considered. In general, one can clearly see that the marginal gain of using an additional day decreases with the number of days considered (see also Fig. 4.10). Similarly, the marginal gain of increasing the resolution also decreases as the resolution increases (this can be seen by connecting the points corresponding to the same number of representative days). Therefore, there will be a trade-off between the number of representative days and the resolution.

From these curves, the efficient frontier can be deduced, i.e., a collection of points for which the highest accuracy corresponding to a specific number of time slices is obtained. From Fig. 4.17, it can be seen that a reasonable number of representative days should be prioritized to using a high resolution. Only once a reasonable number of days is obtained (i.e., the marginal value of increasing the number of days is sufficiently reduced), increasing the resolution becomes relevant. Based on these results for a single region, when the number of time slices of the planning model is restricted to a value below 72, it is advisable to use a low resolution, such that a sufficiently high number of days can be taken into account. Within the range of 72 to 288 time slices, using a number of representative days with a 2-hourly resolution is shown to be optimal. For a higher number of time slices, the resolution can be further increased to hourly values.

While the resolution is shown to have a limited effect on the approximation of the DCs of the original time series, this is not necessarily the case for the other error metrics. Tab. 4.5 shows the impact of the resolution on the different error metrics if all days of the original time series are selected. This gives an indication about the impact of lowering the resolution on the different error metrics. As can be observed, the resolution predominantly influences the quality of the approximation of the short-term dynamic aspects.

Error	Resolution [h]			
Metric	0.25	1	2	4
$NRMSE_{avg}^{DC}$	0	0.1	0.4	1.1
$NRMSE_{avg}^{RDC}$	0	1.1	1.7	2.4
CE_{avg}	0	0.001	0.003	0.009

Table 4.5: Impact of the temporal resolution on the different error metrics in case all days of the original time series are selected.

Test case

This section presents a test case where the sets of representative days obtained by the different approaches are used in a power-system optimization model (PSOM). The resulting capacity mix, costs and computation time will be compared to a reference run using the entire time series.

The PSOM aims to minimize the total discounted system cost. This total system cost comprises investment costs, fixed operations and maintenance (FOM) costs and the costs related to the operation of the power system (consisting of fuel costs, costs related to carbon emissions and start-up costs). The limited flexibility of thermal power plants is modeled via a clustered unit commitment (CUC) formulation. For a comprehensive description of the investment model with integrated CUC constraints, we refer to Section 5.3 of Chapter 5. The problem is relaxed by using continuous rather than integer commitment variables. The PSOM is applied to determine the cost-optimal capacity and generation mix to achieve a 35% share of renewable electrical energy generation in a power system loosely inspired by the Belgian one. In the presented case, it is assumed that no existing generation capacity is present, i.e., the model is run in greenfield mode. It must be stressed that the case presented here is highly simplified and serves only as an illustration of the use and possible implications of using different approaches to select a set of representative days.

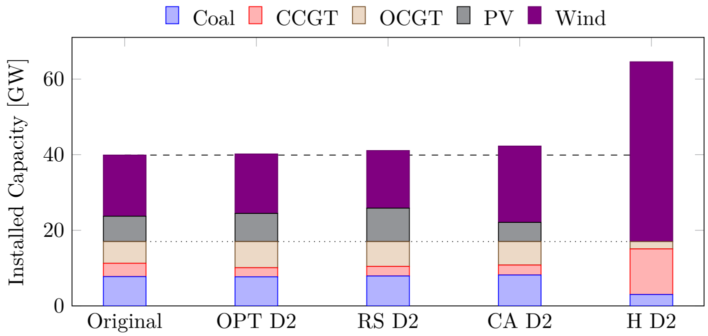
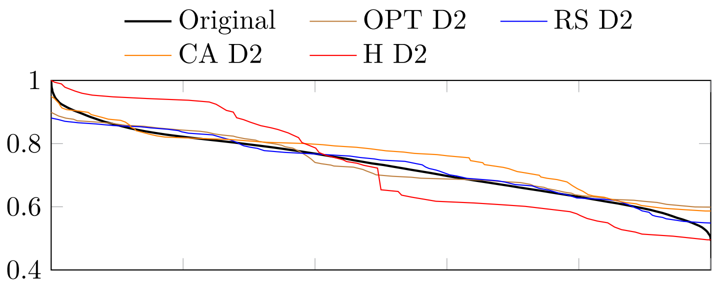


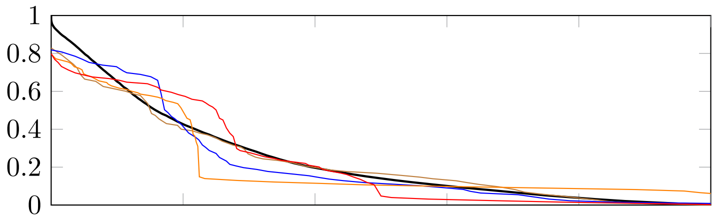
Figure 4.18: Installed capacity in the reference run comprising the entire series, and for the runs using 2 representative days selected by the different approaches.

The capacity mix resulting from the run using the entire time series and the runs using 2 representative days selected by the different approaches are presented in Fig. 4.18. Deviations with respect to the reference case can be observed. For the OPT, RS and CA approach, these differences are relatively minor. In contrast, if the days are selected using the simple heuristics, these differences are very large. Relatively small differences can be observed in the conventional generation mix. It must be noted that, in order to ensure an adequate system, the PSOM has a constraint for the minimum level of dispatchable capacity. The differences in the amount and type of IRES required to meet the renewable energy target are more pronounced. This is related to how well the sets of days approximate the wind and solar generation time series. As can be seen in Fig. 4.19, the days selected by the OPT approach provide a relatively good approximation of the wind and solar generation DCs. In contrast, the days selected by the CA and the H approach have significantly higher deviations, particularly for solar PV generation. Both the CA and H approach underestimate solar generation, leading to fewer investments in solar PV generation and a higher dependence on wind turbines to meet the renewable energy target.

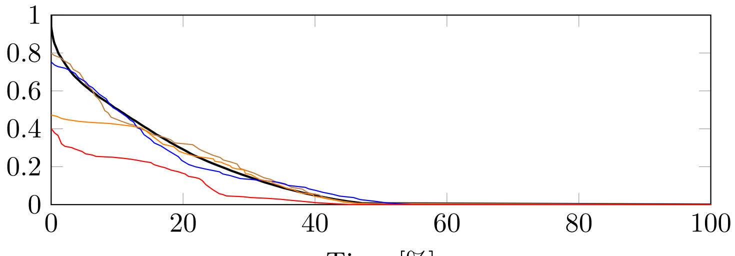
By using only a limited set of historical days, the PSOM has imperfect information regarding the annual cost related to operating any given system. Therefore, the PSOM aiming to minimize the total system cost comprising of both investment and operational costs will not be able to find the global optimum. This is reflected in Fig. 4.18 by the investment decisions deviating from the investment decisions in the reference case. To evaluate this suboptimality, the cost of operating a system with the capacity mix resulting from each model run has been reevaluated using the entire time series. The projected and reevaluated total system costs are presented in Tab. 4.6. The suboptimality is the difference between the reevaluated cost and the cost in the reference case,



(a) Load



(b) Onshore wind generation



(c) Solar PV generation

Figure 4.19: Approximation of the duration curves for 2 representative days selected by the different approaches.

and is presented between brackets as a percentage of the total system cost in the reference case. The results show that by using 2 representative days selected by the OPT approach, this suboptimality equals a mere 0.29% for the presented case. For the best randomly selected combination of days, this suboptimality increases to 0.72%, while for the days selected by the clustering algorithm, the deviation increases to 2.57%. Using the simple heuristics, this suboptimality is significantly higher.

In general, by having a better selected set of days, the model has more accurate information regarding the annual cost of operating any given power system, and is therefore more likely to find a solution close to the global optimum. However, it is important to note that having better information does not necessarily lead to better decision making in every single case. For this reason, the results presented in this test case should not be seen as an attempt to quantify the value that can be added by a better selection of representative days, but rather as an illustration of how the selection of a set of representative days can impact the accuracy of the results and the computation time of ESOMs/PSOMs.

Approach	N_{repr}	Projected cost $[M€/a]$	Re-evaluated cost $[M€/a]$
Orig.	365	7071	7071
OPT	2	7221	7092 (+0.29%)
RS	2	7043	7122 (+0.72%)
CA	2	7389	7253 (+2.57%)
H	2	10041	9441 (+33.51%)

Table 4.6: Overview of the total system costs in the different runs.

An overview of the impact of using representative days on the problem size and the computational cost of the PSOM is presented in Tab. 4.7. Whereas the number of equations and variables increases linearly with the number of time steps in the model, it can clearly be observed that the computational cost increases more than linear with the number of time steps considered in the PSOM. For the presented test case, the runs using 2, 4 and 8 representative days took on average 2.7, 9.3 and 22.0 seconds respectively. In contrast, the reference case took over 50,000 seconds (almost 14 hours).

# repr. days	# Eq.	# Var.	Comp. time	Speed-up
Orig. (365)	3188,658	1646,910	50476	-
2	17,480	9,054	2.7	18439
4	34,932	18,078	9.3	5419
8	69,836	36,126	22.0	2298

Table 4.7: Overview of the problem size and the computational performance of the models using a varying number of representative days. The number of equations and variables as well as the average computation time and speed-up are presented. Computation times are expressed in seconds. Speed-ups are expressed relative to the reference model (Orig.) which uses the time series of an entire year of data.

4.4 Summary and conclusions

To limit the computational complexity of energy-system optimization models (ESOMs), intra-annual variations in demand and supply are typically modeled using a low number of so-called time slices. These time slices are typically set up to represent seasonal, daily and diurnal fluctuations in demand and supply. Within each time slice, the load and intermittent renewable energy sources (IRES) availability is constant and typically taken equal to the average value corresponding to that time slice (e.g., winter days). In Chapter 3, it was shown that such a temporal representation leads to smoothing of wind and solar generation output. As a result, ESOMs relying on such a temporal representation significantly underestimate the challenges related to the integration of large shares of IRES.

In this chapter, we have considered a number of fundamentally different time-slicing methods to improve the temporal representation in ESOMs. These different time-slicing methods are evaluated by analyzing how well each time-slicing method approximates the residual load duration curve (RLDC) for a varying penetration of IRES.

A first method aims to better capture the characteristics of IRES by increasing the temporal resolution, i.e., the number of diurnal time slices. This method has received a lot of attention in the recent literature. However, our results indicate that simply increasing the temporal resolution (and hence the total number of time slices) does not significantly improve the temporal representation. The reason is that solar and particularly wind output is still leveled out by averaging over multiple days.

An alternative time-slicing method involves slicing the joint probability distribution of the load and IRES generation time series. In this method, called the enhanced integral (EI) method here, the time slices no longer correspond to specific seasons, day-types or diurnal periods, but rather represent moments of high/low demand and high/low IRES availability. The load and IRES availability assigned to each time slice is still the result of averaging data. However, following from how the time slices are defined, the data corresponding to each time slice is similar in terms of load and IRES availability. Therefore, the averaging does not significantly smooth the IRES availability. Our analysis shows that by using the EI time-slicing method, the RLDC can be accurately represented while using only a low number of time slices (e.g., 12). The main drawback of using the EI time-slicing method is that chronology is not preserved. Therefore, this method might not be suited to assess the impact of short-term dynamic variations of the residual load, and the potential/requirement of different flexibility options, such as energy storage technologies, to deal with these variations.

A final time-slicing method is based on selecting a number of representative historical periods (e.g., days or weeks). Since in this method, only the data of a small number of historical periods is used, there is no smoothing of load and IRES availability. Our results show that this method is capable of approximating the RLDC with a similar accuracy as the EI method (for the same number of time slices). In addition, this method has the additional advantage of preserving chronology (in contrast to the EI time-slicing method). However, the results indicate that the quality of this time-slicing method is strongly dependent on the selected set of representative periods, and care is needed in selecting a representative set of periods.

To select a representative set of historical periods, multiple approaches have been used in the literature. Typically, either simple heuristics or clustering algorithms are applied.

In this chapter, a novel optimization-based approach for selecting a representative set of historical periods relying on mixed integer linear programming (MILP) and a derived hybrid approach are presented. The results of these approaches for selecting representative days are compared to a number of approaches available in the literature. Different temporal aspects which can impact the results of ESOMs/power-system optimization models (PSOMs) were identified and appropriate metrics were proposed to assess how well these aspects are represented by a set of representative periods.

The results of our analysis shows that the developed optimization-based approach and the derived hybrid approach for selecting representative days obtain more accurate results than the approaches available in the current literature. The significance is that by applying these novel approaches to select a set of representative periods, the accuracy of ESOMs/PSOMs can be increased without increasing the computational cost. This is illustrated in a simplified test case aiming to determine the cost-optimal capacity mix to obtain a target share of renewable electricity generation in a system inspired by the Belgian electrical power system. However, the developed approaches also have the disadvantage that solving these approaches themselves can be computationally costly and require some implementation effort.

Finally, the trade-off between the temporal resolution and the number of representative days has been investigated. Our results indicate that whenever a low number of time slices can be used (12-72), it is better to use a rather low temporal resolution (e.g., 4-hourly) in order to make sure that a higher number of representative days can be selected without increasing the computational cost. As the number of time slices is increased, the used resolution can be increased. However, our results indicate that using an hourly resolution only becomes worthwhile whenever more than 288 time slices are used.

The work presented in this chapter has a number of limitations, each motivating further research. First, we have assumed that appropriate metrics which drive the results of ESOMs/PSOMs could be defined up front. Analyzing the relationship between the proposed metrics and the accuracy of approximating the results generated by ESOMs/PSOMs would be an interesting point for further research. Comparing the results of an ex-post evaluation (i.e., based on metrics to evaluate the approximation of the results generated by an ESOM/PSOM) to the results provided by an ex-ante evaluation (i.e., based on metrics to evaluate the approximation of certain temporal features of the original time series) of the quality of a set of representative periods could expose the need for different or adjusted ex-ante metrics, which can be used to further enhance the selection of a set of representative periods.

Second, we have focused on approximating relevant time series within one country/node. However, most ESOMs and PSOMs consider multiple countries/nodes. Accurately modeling the temporal dimension in models with a high number of regions (e.g., models covering Europe) is challenging. This because, first of all, the load and IRES time series in each modeled region should be accurately represented by a single set of representative periods. Second, next to the correlation between different time series within a single region (e.g., wind and load in region A), also the correlation between the time series in different regions (e.g., wind in country A and wind in country B) becomes relevant to capture in a multi-regional model. To accurately model all these aspects, it is likely that a higher number of representative periods will be needed in a multi-regional model. However, multi-regional models already tend to have a higher computational cost. Given these difficulties, future research is needed to evaluate the proposed time-slicing methods for models with multiple countries/nodes.

Third, the time-slicing method based on selecting representative periods has been shown to accurately approximate the RLDC while at the same time preserving chronology within each selected period. However, the impact of such a time-slicing method on the modeling of storage technologies has not been investigated. Particularly for storage technologies which can store large amounts of energy, there can be significant arbitrage opportunities between the different representative periods. Opportunities to ensure that the value of storage technologies is accurately reflected exist both in the selection of the representative periods (in the presented work no selection criterion has been used for medium-term fluctuations) and in the way these different representative periods are coupled in the ESOM/PSOM. A preliminary analysis performed in a masters thesis indicates that improvements can be obtained by adding an additional criterion to the selection of the representative periods. In the selection, the criterion could already account for how the different representative periods are coupled in the ESOM/PSOM. Further research is needed to further develop and validate such methods.

Finally, we have shown that when only a low number of time slices can be used and representative days are selected, it is more efficient to reduce the temporal resolution in order to increase the number of days that can be selected. In this work, we have reduced the temporal resolution by dividing each day in a number of equally long time slices (e.g., 2-hourly, 4-hourly). However, there are opportunities to more efficiently divide a day to a predefined number of time slices. This can further improve the time-slicing method based on selecting a number of representative historical periods.

Chapter 5

Improved technical representation in planning models

This chapter focuses on considering technical constraints in overall energy-system optimization models (ESOMs) and power-system optimization models (PSOMs). These technical constraints comprise both system-level constraints (e.g., the need for operating reserves) and plant-level constraints (e.g., limited ramping rates). As shown in Chapter 3, neglecting technical constraints in ESOMs/PSOMs contributes to underestimating the challenges related to the integration of intermittent renewable energy sources (IRES) and introduces a technology bias towards baseload technology-types and IRES, while flexible technology-types are not sufficiently valued.

In Chapter 3, we furthermore argued that the impact of neglecting technical constraints is dependent on both the level of IRES (demanding flexibility), the thermal generation fleet and other sources of flexibility (providing flexibility). In addition, the flexibility that can be provided by the thermal generation fleet depends on the cycling characteristics of these technology-types, for which a wide range of values is reported in the literature. Therefore, the first goal of this chapter is to gauge the significance of incorporating technical constraints for a variety of capacity mixes and assumptions regarding the flexibility of thermal power plants and the availability of other sources of flexibility.

Ideally, ESOMs and PSOMs would integrate the detailed technical constraints typically considered in operational unit commitment (UC) models. However, this would be computationally infeasible. Therefore, the second main goal of this chapter is to derive and evaluate reduced, less computationally demanding, formulations of the set of technical constraints typically considered in UC models. To this end, we first analyze in detail (i) which specific constraints have a significant impact on the results, and (ii) how these specific constraints impact results. Subsequently, this information is used to derive a number of reduced formulations of the UC problem, which can be tractably integrated in planning models. These reduced formulations are finally evaluated in terms of accuracy and computational cost.

The outline of the remainder of this chapter is as follows. First, Section 5.1 presents a review of ESOMs and PSOMs which consider technical constraints in one way or another. Next, Section 5.2 presents the methodology used to evaluate the impact of having a simplified technical representation. In addition, the data used and the main assumptions are presented in this section. The modeling framework that is developed and used within this chapter is presented in Section 5.3. After that, the results are presented in Section 5.4. This section comprises the results regarding the relevance of incorporating technical constraints in planning models, the results regarding the impact/role of specific technical constraints and the results regarding the derived reduced clustered unit commitment (CUC) model formulations. Finally, a summary and an overview of the main conclusions are provided in Section 5.5.

This chapter includes elements from:

- Meus, J., Poncelet, K., and Delarue, E. *Applicability of a clustered unit commitment model in power system modeling.* IEEE Transactions on Power Systems, 99 (2017)

5.1 Literature review

As discussed in Chapter 3, most ESOMs do not incorporate technical constraints (see e.g., [111, 148, 149]). This implies that different technology-types can be dispatched freely and the dispatch will hence follow the merit order (MO). In a number of ESOMs, technical constraints are to some extent accounted for. In addition, the level of technical detail in PSOMs is typically somewhat higher. Below, we provide an overview of the methods used in state-of-the-art ESOMs and PSOMs. The discussion is based on an in-depth review of the ESOMs and PSOMs listed in Tab. 5.1.

Model	Author	Scope
MESSAGE model	Sullivan et al. [150] (International Institute for Applied Systems Analysis)	Global energy system, agriculture and forestry
JRC-EU-TIMES model	Simoes et al. [111] (Joint Research Centre, European Commission)	Energy system EU 28 + neighbouring countries, 2005-2050
NETPLAN model	Krishnan et al. [149] (Iowa State University)	Power and transportation system, U.S., 40-year time horizon
-	Aboumahboub et al. [151] (Technical University of Munich)	Global power system, single year
LIMES-EU model	Nahmmacher et al (Potsdam Institute for Climate Impact Research) [85]	EU power system, 2010-2050
PowerACE-Europe	Pfluger and Wietschel [148] (Fraunhofer Institute for Systems and Innovation Research)	EU 27 + Norwegian + Swiss power system, multiple decade time horizon
PERSEUS-RES-E model	Rosen [45] (Karlsruhe University)	EU 15, 20-year time horizon
ReEDS model	Short et al. [84] (National Renewable Energy Laboratory)	U.S. power system, sequential optimiziation in 2-year time steps
EMMA model	Hirth [152] (Neon)	Northwestern European power system, single year
Swiss TIMES electricity systems model (STEM-E)	Kannan and Turtion [113] (Paul Scherrer Institute)	Swiss electricity system, 2000-2110
OSeMOSYS enhanced	Welsch et al. [128, 127]	illustrative power system, single year

Resource planning model (RPM)	Mai et al. [87, 130] (National Renewable Energy Laboratory)	Power system of Colorado, Utah, Wyoming and New Mexico, sequential optimization runs with 5-year time step each
SWITCH model	Fripp [86] (University of California, Berkeley)	Power system California, 16-year time horizon
-	De Jonghe et al. [114] (University of Leuven)	illustrative power system, single year
-	van Stiphout et al. [22] (University of Leuven)	Illustrative power system, single year
-	Palmintier and Webster [153, 88, 154, 8] (Massachusetts Institute of Technology)	ERCOT power system, single year
-	Kirschen et al. [48]	IEEE RTS test system, single year
IMRES model	de Sisternes [73] (Massachussets Institute of Technology)	single year
-	Pudjianto et al. [155] (Imperial College London)	UK power system, single year
-	Jin et al. [131] (Iowa State University)	Illinois based power system, single year

Table 5.1: Overview of the reviewed energy and power-system optimization models.

Due to computational restrictions in large-scale planning models, stylized approaches are regularly used to mimic the impact of incorporating detailed technical constraints. One example is the introduction of a so-called flexibility requirement in the MESSAGE model. In this approach, each technology-type is awarded a coefficient between -1 and 1, where positive values represent the flexibility that can be offered by a certain technology-type, and negative values represent the need for flexibility caused by using a certain technology-type. In all time slices, the net availability of flexibility should be positive [150]. Another example can be found in the EMMA model. In this model, the impact of start-up costs of nuclear and coal-fired power plants is simulated by lowering the variable cost of these technology-types. As a result, these generators will tolerate small negative contribution margins before shutting down. To compensate for the fictive reduction of variable costs, the fixed costs are increased accordingly [152, 35].

One very popular stylized approach is to introduce must-run requirements to limit the flexibility of thermal power plants. These must-run requirements restrict changes in power output or online capacity within certain periods. As such, these must-run requirements aim to represent the combined impact of detailed technical constraints and cycling costs. For example, in the Switch model, nuclear and coal-fired power plants are forced to run at constant power output throughout the entire year [86, 112]. Similarly, in certain TIMES models baseload technology-types are defined to operate at a certain time-slice level, which implies that the generation is constant within all time slices at a lower level. For instance, in the Swiss TIMES model STEM-E, nuclear plants are modeled at annual level, implying that nuclear plants generate a constant power output throughout the year [113]. In the PERSEUS-RES-E model, similar constraints are introduced to keep the generation of certain technology-types constant within each season [45]. In the LIMES-EU model, the online/committed capacity cannot change between certain periods (nuclear plants are allowed to change their online capacity only between years, shorter periods apply for coal-fired plants and combined cycle gas turbines (CCGTs)). The power output within a period is then restricted by a minimum loading requirement [85]. Similar constraints can again be found in NREL's Resource Planning Model (RPM) and Regional Energy Deployment System model (ReEDS), as well as in the model developed by De Jonghe et al. [84, 87, 114].

In some models, certain technical constraints are incorporated in a simplified manner without distinguishing between committed (online) capacity and offline capacity. Frequently, the focus is on the provision of upward operating reserves to deal with contingencies and forecast errors. Since no distinction is made between online and offline capacity, no distinction can be made between spinning and non-spinning reserves and the technical constraints restricting the ability to provide spinning/non-spinning reserves. For instance, in the NETPLAN model [149] and the PERSUES-RES-E model [45], the provision of upward reserves by a certain technology-type is restricted by ramping constraints in which the ability to ramp is based purely on the installed capacity of that technology-type. Hence, the ability to provide upward reserves is independent of the dispatch (i.e., the number of online units of that technology-type and the power output level). Such ramping constraints thus help to ensure that the capacity mix is sufficiently flexible to be able to provide the required reserves, but do not ensure that the dispatch is adapted in such a way that the required reserves can actually be provided. Similar ramping constraints, but now between consecutive time steps are incorporated in the model used by Abouhmaboub et al. [151]. Aside from ramping restrictions, a number of models restrict the provision of upward reserves based on the available capacity, i.e., the instantaneous power generation together with the procured reserves should not exceed the installed capacity. Such constraints can for instance be found in the NETPLAN model [149], the PERSEUS-RES-E model [45], and the ReEDS model [84].

Finally, certain PSOMs have integrated detailed UC constraints on a plant-by-plant level (see for instance, the IMRES model [73], the RPM model [87], the model developed by Jin et al. [131], the model developed by Pudjianto et al. [155] and the model developed by Kirschen et al. [48]). The time horizon in these models is typically restricted to a single year or a limited number of years. In addition, to make the models computationally tractable, a year is typically represented by a number of representative weeks or days. Recently, Palmintier and Webster [8, 156] have developed an investment model with integrated unit commitment constraints in which identical plants are grouped into clusters. This allowed replacing the binary commitment variables for a number of identical power plants by a single integer commitment variable. This was shown to significantly reduce the computational cost. In the model used in van Stiphout et al. [22], similar clustered unit commitment constraints were integrated, but the problem was further relaxed by using continuous rather than integer commitment variables.

To conclude, a wide variety of approaches to represent or mimic technical constraints in ESOMs and PSOMs have recently been used. These approaches vary from highly stylized to very detailed. Whereas the models directly integrating UC constraints are highly detailed, they require a lot of computational resources. In contrast, the more simplified and stylized approaches are computationally lean, but might not be very accurate.

5.2 Methodology

5.2.1 General Methodology

To assess the impact of incorporating a simplified technical representation, the results of a PSOM with the simplified technical representation are compared to a reference PSOM. This reference PSOM integrates a CUC model. This reference model uses integer variables to keep track of the number of online units within each technology-type cluster and incorporates minimum up and down time

(MUDT) constraints, start-up costs (SC), part-load efficiency losses (PLEL), minimum stable operating point (MSOP) restrictions, ramping constraints as well as operating reserve requirements. The formulation of PSOM with integrated CUC constraints is presented in Section 5.3.

The results of the model with a limited level of technical detail and the reference model will first of all be compared in terms of the projected total annual system cost and the capacity mix. Since all models with a limited level of technical detail considered here are relaxations of the integrated investment and CUC model, these models will underestimate the technical challenges related to the operation of the power system and therefore underestimate the total system cost. In addition to the projected total system cost, the suboptimality induced by not incorporating detailed technical constraints in the planning model will be evaluated. To this end, the capacity mix resulting from the model with a low level of technical detail will be fixed and the operational costs (i.e., all costs except those which are directly related to the investment decisions) are reevaluated using the full CUC model. These reevaluated operational costs together with the investment related costs will be called the "effective total system cost" here. The suboptimality induced by incorporating only a low level of technical detail then corresponds to the difference in effective total system cost[1]. The methodology is schematically presented in Fig. 5.1.

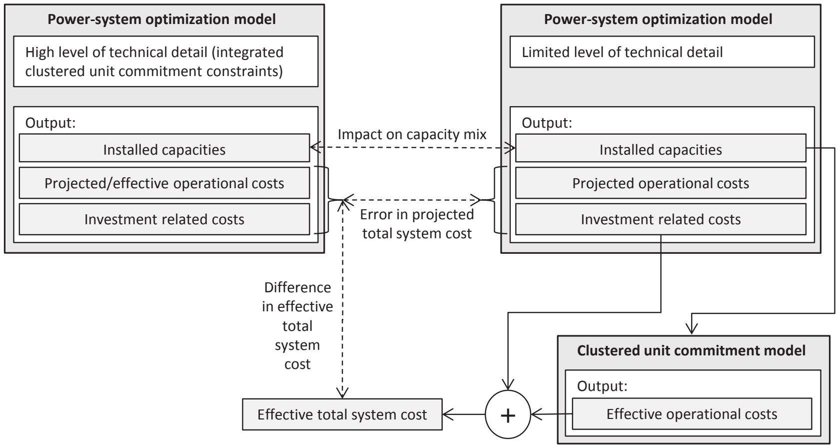


Figure 5.1: Schematic overview of the methodology employed for evaluating the impact of using lower levels of technical detail.

[1]Note that for the reference PSOM, the projected and effective total annual system cost are identical.

In the case the impact of neglecting technical constraints altogether is analyzed, the term 'limited level of technical detail' refers to not considering any technical constraints. In this case, the instantaneous power generation of a technology-type is only restricted by the available capacity. This implies that, technology-types will be dispatched according to the MO list until either the technology-type is generating at maximal capacity or demand is fulfilled. We therefore refer to the model which does not incorporate technical constraints as the MO model. To assess the impact of neglecting a specific technical constraint, the model with the limited level of technical constraints incorporates the full CUC model with the exception of this specific constraint. Below, the list of all considered models with different levels of technical detail is presented. In the results section, we will refer to these models according to the name presented between brackets. The different reduced model versions will be introduced in Section 5.4.4 and are not included here.

- All technical constraints (REF)
- No technical constraints (MO)
- All technical constraints except minimum up and down time constraints (no MUDT)
- All technical constraints but not considering start-up costs (no SC)
- All technical constraints but not considering part-load efficiency losses (no PLEL)
- All technical constraints except minimum stable operating point constraints (no MSOP)
- All technical constraints except ramping constraints (no RAMP)
- All technical constraints except operating reserve constraints (no RES)

To analyze the relationship between the penetration level of IRES and the thermal generation fleet, on the one hand, and the impact of technical constraints, on the other hand, 4 different scenarios are considered, which are presented in Tab. 5.2. Scenario A and B both are scenarios with a low penetration of IRES. Whereas scenario A has nuclear plants as baseload generation, scenario B does not. Scenario C and D both have a high penetration of IRES. Scenario D again has nuclear generation as baseload whereas scenario C does not. To achieve these different capacity mixes, the tax for greenhouse gas (GHG) emissions and the support for IRES are varied.

In addition to the different scenarios, we consider 2x2 different cases. Each case represents a different level of available flexibility. A first distinction is

Scenario	A	B	C	D
Description	low IRES, nuclear baseload	low IRES, no nuclear	high IRES, no nuclear	high IRES, nuclear baseload
$T^{GHG}[EUR/ton]$	0	0	30	100
$S^{IRES}[EUR/MWh]$	0	0	50	50
Technology-types excluded	-	nuclear	-	-

Table 5.2: Overview of the considered scenarios. The scenarios differ in terms of the applied tax for GHG emissions (T^{GHG}) and the support for intermittent renewable energy sources (S^{IRES}). Additionally, in scenario B, investments in nuclear plants are not allowed. In scenario C, the model can invest in nuclear plants, but it will not do so due to the high penetration of IRES reducing the number of operating hours.

based on the flexibility of thermal power plants. As discussed in [6], there is a large range of data regarding the cycling characteristics of thermal power plants. We consider two sets of cycling characteristics. In the first set, the flexibility of thermal power plants is near the lower limit of the ranges reported in the literature (referred to as the low flex case) while in the second set, the flexibility of thermal power plants is assumed to be near the upper limit of the ranges specified in the literature (referred to as the high flex case). The cycling characteristics adopted in both cases are presented in Tab. 5.4. For both these cases, we consider a case with or without the opportunity to invest in electricity storage technology-types. Cases in which investments in storage technology-types are considered are indicated by a trailing S. An overview of the 4 considered cases is presented in Tab. 5.3.

Case	low flex	high flex	low flex S	high flex S
Flexibility of thermal power plants	low	high	low	high
Investments in storage allowed	no	no	yes	yes

Table 5.3: Overview of the considered cases representing different levels of available flexibility.

5.2.2 Data and assumptions

All simulations are done for a system inspired by the German electricity system for the year 2050. Furthermore, the optimization model is used in a greenfield mode, meaning that the focus is on a single year and no existing capacity is considered. It must be noted that restricting the scope to a single region and a single year are strong assumptions which should be avoided when applying PSOMs or ESOMs to gain insights into the transition of the electrical power/energy system. However, in this work, the focus is on a methodological analysis aiming to assess the impact of the level of technical detail used in PSOMs/ESOMs. For sake of simplicity and to be able to solve the reference runs (with integrated CUC constraints) with a reasonable optimality gap[2], the scope is restricted to the electrical power system in a single region and a single year.

The capacity factor time series for onshore and offshore wind generation and solar photovoltaic (PV) generation are taken from the EMHIRES data sets [157] for Germany, as provided by the Strategic Energy Technologies Information System (SETIS) of the European Commission. These time series are scaled according to the endogenously determined capacity of wind and PV. The electricity demand time series for Germany are taken from the transparency platform provided by the European Network of Transmission System Operators for Electricity (ENTSO-E) [158]. Changes in the shape of the demand time series, for instance related to the increase in the use of electrical heat pumps or electrical vehicles, are not considered. In addition, the demand is assumed to be inflexible. Finally, to manage the computational complexity, the year is represented by 8 representative weeks, which are selected using the optimization model presented in Section 4.3.3 of the previous chapter.

Data regarding investment costs, fixed and variable operations and maintenance costs, as well as life times and lead times are taken from [111, 119]. Additionally, fuel prices are taken from the new policies scenario from the International Energy Agency's World Energy Outlook 2015 [159]. An exception is made for the fuel related costs for nuclear plants which are adopted from [119]. The data used in the simulations is presented in Tab. B.1-B.4 in Appendix B. A discount rate of 5% is used to annualize the investment costs.

As discussed in [6], different technical characteristics are used for similar generation technology-types in different studies. The range of reported technical characteristics is very broad. In this work, the cycling characteristics of different technology-types are adopted from the range of values presented in [119, 7, 6] and are presented in Tab. 5.4. Due to lack of data regarding the cycling

[2] All simulations are solved using an optimality gap of 0.5%.

characteristics of carbon capture plants, it is assumed that these are identical to the corresponding technology-types without carbon capture. The technical characteristics considered for storage technology-types is based on the data in [160, 119], and is presented in Tab. B.3 in Appendix B.

Technical characteristic	Flexibility case	NUC	COAL SC	CCGT	OCGT
MSOP [$\%/P_{nom}$]	low flex	50	40	50	50
	high flex	40	25	30	20
Eff. loss at MSOP [%pt]	low flex	5	2	11	22
	high flex	1.8	2	3.2	9
Ramp rate [$\%P_{nom}$ /min]	low flex	0.25	0.66	0.83	0.83
	high flex	5	4	10	25
Ramp cost [EUR/ ΔMW]	low flex	0	1.71	0.53	2.02
	high flex	0	1.09	0.22	0.68
MUT [h]	low flex	24	10	6	1
	high flex	0.25	0.25	0.25	0.25
MDT [h]	low flex	24	10	6	1
	high flex	24	3	0.5	0.25
Start-up energy [$MWh_{th}/\Delta MW_e$]	low flex	46.7	3.6	1.8	0.0
	high flex	16.7	3.6	1.5	0.0
Start-up depreciation [EUR/ΔMW_e]	low flex	1.7	70.3	68.4	105.0
	high flex	1.7	45.1	24.5	19.4
Start-up time [h]	low flex	50	8	1	0.33
	high flex	24	2	1	0.17

Table 5.4: Cycling characteristics of the dispatchable technology-types in the low and high flex case. The efficiency, minimum stable operating point (MSOP), efficiency loss at this MSOP, ramping capabilities and corresponding costs, minimum up and down times (MUT/MDT), start-up fuel consumption and depreciation costs as well as annual availability are presented.

For determining the reserve requirements, we have adopted the same assumptions as those made in NREL's Resource Planning Model [161]. Here, the operating reserve requirements vary throughout the year dependent on the demand and the penetration of wind and solar generation. An overview of the adopted reserve requirements is presented in Tab. 5.5. As will be discussed in Section 5.4.3, the assumptions taken regarding the required reserves can have significant implications for the model results for scenarios with a high penetration of IRES.

Both thermal generators and storage technology-types can contribute to the

Reserve type	Sizing	Activation time
Frequency regulation reserves (FRR)	1% of demand	Sub 5 minutes, 100% spin
Spinning contigency reserves (SCR)	Maximum of 6% of demand and the largest contingency	10 minutes, 50% spin
Variable renewable forecast error reserves (VRFER)	10% of wind generation + 7.5% of solar generation	1 hour, 100% spin

Table 5.5: Overview of the reserve requirements integrated in the CUC model. These reserve requirements are taken from NREL's Resource Planning Model [161]. For the case considered here, the spinning contingencies systematically correspond to 6% of the demand.

provision of reserves. Note that due to the time required for starting up thermal power plants, and the requirements for spinning reserves, no non-spinning reserves can be provided by thermal generators. For storage technology-types, in addition to the cycling constraints, it is assumed that upward reserves can only be provided whenever sufficient energy is stored to provide the reserves for a duration equal to twice the activation time. This limitation for the provision of upward reserves by storage technology-types serves to ensure that the reserves can effectively be provided when necessary, even if the reserves need to be fully activated for a duration exceeding the required time for activation[3].

In addition to the operating reserve requirements, a planning reserve margin of 15% with respect to the peak demand is considered. Only dispatchable technology-types are assumed to contribute to the provision of firm capacity.

In the model, it is allowed to procure less than the required level of reserves or even to shed load. However, cost penalties of 3,000 EUR/MWh and 10,000 EUR/MWh are applied for reserve shedding and load shedding, respectively.

[3]The assumption adopted here implies that whenever a certain reserve would be activated consecutively for more than this duration, it cannot be guaranteed that the storage technology will be able to effectively provide the reserves. More robust constraints can be incorporated to ensure that storage technology-types can provide the required reserves in a worst case scenario, see e.g., [162].

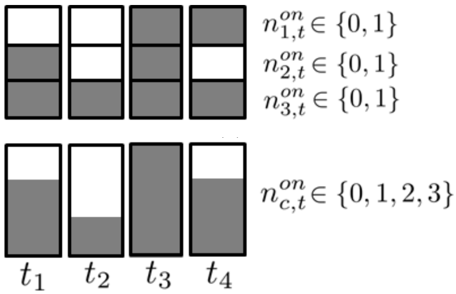
5.3 Model formulation: investment planning with integrated clustered unit commitment constraints

5.3.1 Principle of clustered unit commitment formulations

For longer-term operational problems (e.g., asset valuation [163]) or long-term investment planning problems [156], [154], incorporating traditional unit commitment (UC) constraints for individual power plants is computationally infeasible (or comes at the expense of a strong reduction in the level of temporal, spatial or technological detail [73, 16]). To overcome this issue, so-called clustered unit commitment (CUC) formulations have been formulated and applied (see e.g., [164, 165, 166, 167, 163, 8]). In these formulations, similar power plants are grouped into a cluster. Accordingly, a single integer variable can be used to represent the number of online units within each cluster in each time step. As such, the number of variables and the state space can be strongly reduced compared to traditional UC formulations which use a separate binary variable for every unit in each time step. The concept of clustering similar or identical units is illustrated in Fig. 5.2. Since this example contains a single cluster consisting of three units, the number of potential states in the binary formulation equals $2^3 = 8$ whereas the clustered formulation only contains 4 potential states. This benefit is vastly magnified by an increasing number of units within the cluster. E.g., a cluster comprising 30 individual units only contains 31 possible states in the CUC model, whereas the number of potential states in the binary formulation equals $2^{30} \approx 1.1 \cdot 10^9$. Hence, clustering eases the search through the extensive combinatorial commitment state space by eliminating a large number of identical or very similar commitment decisions. Additionally, clustering also reduces the number of continuous variables and constraints since they now only apply to a small number of clusters rather than the full set of separate generators [88].

5.3.2 Mathematical model formulation

The mathematical formulation of the greenfield investment planning problem with integrated CUC constraints is presented below. The nomenclature can be found at the corresponding section at the outset of the dissertation. Whenever not explicitly mentioned, all variables are continuous and nonnegative.



(b)

Figure 5.2: Illustration of clustering three units in order to reduce the number of variables and the state space. The top blocks represent the commitment states of three individual power plants. The bottom blocks represent the commitment state variable of the cluster of three plants. Here, $n_{c,t}^{on}$ represents the number of online units within a cluster c in time step t.

Objective function

The objective function to minimize is the total annual system cost. This total annual system cost consists of investment costs, fixed operations and maintenance (FOM) costs, fuel and emission related generation costs, variable operations and maintenance (VOM) costs, start-up costs, ramping costs, load-shedding costs and reserve-shedding costs. In addition, the support for IRES forms a negative term in the objective function[4]:

$$\min(c^{inv} + c^{fom} + c^{gen} + c^{vom} + c^{su} + c^{ramp} + c^{ll} + c^{lr} - v^{ires}). \tag{5.1}$$

The investment and FOM costs are directly related to the investments in generation technology-types $g \in \mathcal{G}$ and storage technology-types $s \in \mathcal{S}$:

$$c^{inv} = \sum_{g \in \mathcal{G}} (cap_g C_g^{INV}) + \sum_{s \in \mathcal{S}} (cap_s C_s^{INV,CAP} + cap_s^e C_s^{INV,EN}), \tag{5.2}$$

$$c^{fom} = \sum_{g \in \mathcal{G}} (cap_g C_g^{FOM}) + \sum_{s \in \mathcal{S}} (cap_s C_s^{FOM}). \tag{5.3}$$

All other terms together form the operational costs. The annual operational cost is approximated via a number of representative historical periods $p \in \mathcal{P}$. Each representative historical period p is assumed to be repeated a number of

[4]From a system perspective, this can be interpreted as there being a constant societal value for renewable electricity generation. From a market perspective, this can be interpreted as a direct subsidy for renewable electricity generation.

times W_p within a typical year. The fuel and emission related generation costs follow from a linearized cost curve for dispatchable generation technology-types $gd \in \mathcal{GD}$, which accounts for part-load efficiency losses:

$$c^{gen} = \sum_{p \in \mathcal{P}} \Big(W_p \sum_{t \in \mathcal{T}} \big(\sum_{gd \in \mathcal{GD}} (n^{on}_{gd,p,t} NC_{gd} \Delta_t + g_{gd,p,t} MC_{gd} \Delta_t) \big) \Big). \tag{5.4}$$

In contrast, the VOM costs are assumed to be directly proportional to the generated electrical energy:

$$c^{vom} = \sum_{p \in \mathcal{P}} \Big(W_p \sum_{t \in \mathcal{T}} \big(\sum_{g \in \mathcal{G}} (gen_{g,p,t} C^{VOM}_g \Delta_t + p^c_{s,p,t} C^{VOM}_s \Delta_t) \big) \Big). \tag{5.5}$$

The start-up and ramping costs respectively follow from:

$$c^{su} = \sum_{p \in \mathcal{P}} \Big(W_p \sum_{t \in \mathcal{T}} \big(\sum_{gd \in \mathcal{GD}} (n^{su}_{gd,p,t} C^{SU}_{gd}) \big) \Big), \tag{5.6}$$

$$c^{ramp} = \sum_{p \in \mathcal{P}} \Big(W_p \sum_{t \in \mathcal{T}} \big(\sum_{gd \in \mathcal{GD}} (ramp_{gd,p,t} C^{RAMP}_{gd}) \big) \Big). \tag{5.7}$$

As stated in Section 5.2.2, the model allows to shed load or not provide the required operating reserves. However, this will be penalized:

$$c^{ll} = \sum_{p \in \mathcal{P}} \Big(W_p \sum_{t \in \mathcal{T}} \big(ll_{p,t} VOLL \Delta_t \big) \Big), \tag{5.8}$$

$$c^{lr} = \sum_{p \in \mathcal{P}} \Big(W_p \sum_{t \in \mathcal{T}} \sum_{r \in \mathcal{R}} \big(lr_{r,p,t} VOLR \Delta_t \big) \Big). \tag{5.9}$$

Finally, the support for electrical energy generated by intermittent renewable generators $gr \in \mathcal{GR}$ is determined as follows:

$$v^{ires} = \sum_{p \in \mathcal{P}} \Big(W_p \sum_{t \in \mathcal{T}} \big(\sum_{gr \in \mathcal{GR}} (gen_{gr,p,t} S \Delta_t) \big) \Big). \tag{5.10}$$

System constraints

A number of system constraints need to be fulfilled. First and foremost, supply and demand of electricity must be in balance at all times:

$$\sum_{g \in \mathcal{G}} gen_{g,p,t} + \sum_{s \in \mathcal{S}} p^d_{s,p,t} + ll_{p,t} = D_{p,t} + \sum_{s \in \mathcal{S}} p^c_{s,p,t} \quad \forall p \in \mathcal{P}, t \in \mathcal{T}. \tag{5.11}$$

In addition, a planning reserve margin is introduced to ensure generation adequacy. In the current model, only thermal power plants contribute to the planning reserve margin:

$$\sum_{gd \in \mathcal{GD}} cap_{gd} \geq \overline{D}(1 + PM). \tag{5.12}$$

To deal with contingencies and forecast errors in demand and supply, different types of operating reserves need to be procured. The operating reserves are assumed to be proportional to the demand and scheduled intermittent renewable electricity generation (as specified in Tab. 5.5). Only upward reserves are considered[5]. In addition, only thermal generators and storage technology-types are allowed to provide upward reserves[6]:

$$\sum_{gd \in \mathcal{GD}} r^{+}_{r,gd,p,t} + \sum_{s \in \mathcal{S}} r^{+}_{r,s,p,t} + lr_{r,p,t} \geq \tag{5.13}$$

$$R^{DEM}_{r} D_{p,t} + \sum_{gr \in \mathcal{GR}} (R^{FE}_{r,gr} gen_{gr,p,t}) \quad \forall r \in \mathcal{R}, p \in \mathcal{P}, t \in \mathcal{T}. \tag{5.14}$$

For each reserve category, a certain fraction needs to be provided by spinning units (as specified in Tab. 5.5):

$$\sum_{gd \in \mathcal{GD}} r^{+,spin}_{r,gd,p,t} + \sum_{ss \in \mathcal{SS}} r^{+}_{r,ss,p,t} + \sum_{sm \in \mathcal{SM}} (r^{+,spin,c}_{r,sm,p,t} + r^{+,spin,d}_{r,sm,p,t}) \geq$$

$$S^{SPIN}_{r} \Big(R^{DEM}_{r} D_{p,t} + \sum_{gr \in \mathcal{GR}} (R^{FE}_{r,gr} gen_{gr,p,t}) - lr_{r,p,t} \Big) \quad \forall r \in \mathcal{R}, p \in \mathcal{P}, t \in \mathcal{T}. \tag{5.15}$$

For storage technology-types, it is assumed that all reserves provided by battery energy storage systems (BESS) $ss \in \mathcal{SS}$ are sufficiently fast for the provision of spinning reserves.

Thermal power plants

Maintenance

The power generation of thermal power plants is constrained by the installed capacity and technical constraints. First of all, scheduled as well as unplanned

[5] Ensuring sufficient downward reserves is typically less expensive than ensuring upward reserves [161].

[6] We come back to this assumption in Section 5.4.3.

outages are taken into account in a stylized fashion by derating the installed capacity with an availability factor $AF_{gd/s}$:

$$cap_{gd}^{av} \leq AF_{gd} cap_{gd} \quad \forall gd \in \mathcal{GD}. \tag{5.16}$$

The available number of units is directly proportional to the available capacity:

$$n_{gd}^{av} \leq \frac{cap_{gd}^{av}}{\overline{P}_{gd}} \quad \forall gd \in \mathcal{GD}. \tag{5.17}$$

Finally, the number of online units, together with those procured to provide non-spinning reserves are restricted by the available units:

$$n_{gd,p,t}^{on} + n_{gd,p,t}^{+,ns} \leq n_{gd}^{av} \quad \forall gd \in \mathcal{GD}, p \in \mathcal{P}, t \in \mathcal{T}. \tag{5.18}$$

Logical conditions

The number of online/spinning units can be changed by starting up or shutting down a number of units:

$$n_{gd,p,t+1}^{on} = n_{gd,p,t}^{on} + n_{gd,p,t}^{su} - n_{gd,p,t}^{sd} \quad \forall gd \in \mathcal{GD}, p \in \mathcal{P}, t \in \mathcal{T}. \tag{5.19}$$

Finally, the discrete nature of power plants is reflected by restricting the variables representing a number of units to natural numbers, i.e., integer variables are used:

$$n_{gd}^{av}, n_{gd,p,t}^{on}, n_{gd,p,t}^{su}, n_{gd,p,t}^{sd}, n_{gd,p,t}^{+,ns} \in \mathbb{Z}_0^+ \quad \forall gd \in \mathcal{GD}, p \in \mathcal{P}, t \in \mathcal{T}. \tag{5.20}$$

Generation level constraints

The power plant output is defined as:

$$gen_{gd,p,t} = n_{gd,p,t}^{on} \underline{P}_{gd} + g_{gd,p,t} \quad \forall gd \in \mathcal{GD}, p \in \mathcal{P}, t \in \mathcal{T}. \tag{5.21}$$

This constraint ensures that whenever a plant is online/spinning, it must be operated above a certain minimum power output (i.e., the MSOP). In addition, the maximum power output is restricted by the rated power:

$$\begin{aligned} gen_{gd,p,t} + \sum_{r \in \mathcal{R}} r_{r,gd,p,t}^{+,spin} \leq {} & (n_{gd,p,t}^{on} - n_{gd,p,t-1}^{su} - n_{gd,p,t}^{sd}) \overline{P}_{gd} \\ & + n_{gd,p,t-1}^{su} SU_{gd} + n_{gd,p,t}^{sd} SD_{gd} \quad \forall gd \in \mathcal{GD}, p \in \mathcal{P}, t \in \mathcal{T}. \end{aligned} \tag{5.22}$$

In the above constraint, the maximum power output of units which have been online in the previous time step and remain to be online in the following time step is restricted by the rated power output, whereas directly after a start-up and before a shut-down, the maximum power is constrained to SU_{gd} and SD_{gd} respectively. This constraint also makes sure that whenever spinning reserves are procured, sufficient head room is available.

Ramping constraints

Changes in generation level are constrained by ramping limits. In a CUC formulation, the power output can be adapted by changing the power output of spinning units, starting up additional units and shutting down units simultaneously. Therefore, the ramping constraint needs to be adjusted correspondingly. In addition, the possible activation of spinning reserves affects the ramp, and is therefore taken into account. The upward and downward ramping constraints respectively become:

$$gen_{gd,p,t+1} - gen_{gd,p,t} + \sum_{r\in\mathcal{R}} r^{+,spin}_{r,gd,p,t+1} \leq (n^{on}_{gd,p,t} - n^{sd}_{gd,p,t})\overline{P}_{gd}\frac{R_{gd}}{100}\Delta_t$$

$$- n^{sd}_{gd,p,t}\underline{P}_{gd} + n^{su}_{gd,p,t}SU_{gd} \quad \forall gd \in \mathcal{GD}, p \in \mathcal{P}, t \in \mathcal{T}, \tag{5.23}$$

$$gen_{gd,p,t} - gen_{gd,p,t+1} + \sum_{r\in\mathcal{R}} r^{+,spin}_{r,gd,p,t} \leq (n^{on}_{gd,p,t} - n^{sd}_{gd,p,t})\overline{P}_{gd}\frac{R_{gd}}{100}\Delta_t$$

$$- n^{su}_{gd,p,t}\underline{P}_{gd} + n^{sd}_{gd,p,t}SD_{gd} \quad \forall gd \in \mathcal{GD}, p \in \mathcal{P}, t \in \mathcal{T}, \tag{5.24}$$

Due to the fact that in a CUC formulation, the power ramps do not directly follow from the changes in total power output, the ramps need to be determined for assigning ramping costs:

$$ramp_{gd,p,t} \geq gen_{gd,p,t+1} - gen_{gd,p,t}$$

$$+ n^{sd}_{gd,p,t}\underline{P}_{gd} - n^{su}_{gd,p,t}SU_{gd} \quad \forall gd \in \mathcal{GD}, p \in \mathcal{P}, t \in \mathcal{T}, \tag{5.25}$$

$$ramp_{gd,p,t} \geq gen_{gd,p,t} - gen_{gd,p,t+1}$$

$$+ n^{su}_{gd,p,t}\underline{P}_{gd} - n^{sd}_{gd,p,t}SD_{gd} \quad \forall gd \in \mathcal{GD}, p \in \mathcal{P}, t \in \mathcal{T}, \tag{5.26}$$

Minimum up and down time constraints

Minimum up and down time constraints respectively force units starting up/shutting down to remain online/offline for a minimum amount of time. These constraints are formulated as follows:

$$n^{sd}_{gd,p,t} \leq n^{on}_{gd,p,t} - \sum_{t'=1}^{MUT-1} n^{su}_{gd,p,t-t'} \quad \forall gd \in \mathcal{GD}, p \in \mathcal{P}, t \in \mathcal{T}, \tag{5.27}$$

$$n^{su}_{gd,p,t} + \sum_{r\in\mathcal{R}} n^{+,ns}_{gd,p,t} \leq n^{av}_{gd} - n^{on}_{gd,p,t}$$

$$- \sum_{t'=1}^{MDT-1} n^{sd}_{gd,p,t-t'} \quad \forall gd \in \mathcal{GD}, p \in \mathcal{P}, t \in \mathcal{T}. \tag{5.28}$$

Eq. (5.27) can be read as the number of units shutting down is restricted to the online units which were not recently started up. Similarly, Eq. (5.28) can be read as the number of units starting up is restricted to the available offline units which were not recently shut down.

Provision of reserves

The upward reserves provided by thermal generators consist of both spinning and non-spinning reserves:

$$r^{+}_{r,gd,p,t} = r^{+,spin}_{r,gd,p,t} + r^{+,ns}_{r,gd,p,t} \quad \forall r \in \mathcal{R}, gd \in \mathcal{GD}, p \in \mathcal{P}, t \in \mathcal{T}. \tag{5.29}$$

The provision of spinning reserves is constrained by the available head room on the one hand (see Eq. (5.22)), and the ability to ramp within the required time for activation. A single generator can provide multiple types of reserve requirements in a given time step. In this case, the ramping capability of this generator must be sufficient to cover the ramps required for the provision of the different types of reserves. For simplicity, we assume that the ramping constraint for a given type of reserves is not significantly impacted by possible ramps that need to be realized for slower types of reserves. This implies that for the fastest reserve type, only the reserves procured for this reserve type need to be considered for the ramping constraint. For the other reserve types, the reserves procured for faster reserve types are also taken into consideration.

$$\sum_{r \in \mathcal{R}: T^{ACT}_{r} \leq T^{ACT}_{r'}} r^{+,spin}_{r,gd,p,t} \leq (n^{on}_{gd,p,t} - n^{sd}_{gd,p,t}) \overline{P}_{gd} \frac{R_{gd}}{100} T^{ACT}_{r'}$$

$$\forall r' \in \mathcal{R}, gd \in \mathcal{GD}, p \in \mathcal{P}, t \in \mathcal{T}. \tag{5.30}$$

Finally, the provision of non-spinning (fast-starting) reserves is constrained to those technology-types for which the start-up time is below the required activation time:

$$\sum_{r \in \mathcal{R}: T^{ACT}_{r} < SUT_{gd}} r^{+,ns}_{r,gd,p,t} = 0 \quad \forall gd \in \mathcal{GD}, p \in \mathcal{P}, t \in \mathcal{T}. \tag{5.31}$$

For units starting up sufficiently fast, the reserves are constrained by the rated power:

$$\sum_{r \in \mathcal{R}: T^{ACT}_{r} \geq SUT_{gd}} r^{+,ns}_{r,gd,p,t} \leq n^{+,ns}_{gd,p,t} \overline{P}_{gd} \quad \forall gd \in \mathcal{GD}, p \in \mathcal{P}, t \in \mathcal{T}. \tag{5.32}$$

Intermittent renewable energy sources

For IRES, the power generation is constrained by the availability of the resource (i.e., wind or solar irradiation). Curtailment is allowed whenever necessary or cost-effective:

$$gen_{gr,p,t} + curt_{gr,p,t} = cap_{gr} CF_{gr,p,t} \quad \forall gr \in \mathcal{GR}, p \in \mathcal{P}, t \in \mathcal{T}. \tag{5.33}$$

Storage technologies

For storage technology-types, separate investments can be made for power capacity (charging and discharging facilities) and energy capacity. However, for each storage technology, the ratio between power and energy capacity is bound to certain limits, specified via a minimal and a maximal discharge duration:

$$\frac{cap_s}{\eta_s} \overline{DUR}_s \geq cap_s^e \geq \frac{cap_s}{\eta_s} \underline{DUR}_s \tag{5.34}$$

The charging and discharging capacity is assumed to be identical.

Since battery energy storage systems (BESS) do not have a minimum operating point and individual units are small, no commitment variables are used to model BESS. In contrast, for pumped hydro storage (PHS) technology-types, integer commitment variables are used (see Eq. (5.42)).

Maintenance

Again, scheduled as well as unplanned outages are taken into account in a stylized fashion by derating the installed capacity with an availability factor AF_s:

$$cap_s^{av} \leq AF_s cap_s \quad \forall s \in \mathcal{S}. \tag{5.35}$$

For PHS, the available number of charging/discharging units is directly proportional to the available capacity:

$$n_{sm,p,t}^{c,av} \leq \frac{cap_{sm}^{av}}{\overline{P}_{sm}} \quad \forall sm \in \mathcal{SM}, \tag{5.36}$$

$$n_{sm,p,t}^{d,av} \leq \frac{cap_{sm}^{av}}{\overline{P}_{sm}} \quad \forall sm \in \mathcal{SM}. \tag{5.37}$$

The available units in turn restrict the number of online charging/discharging units:

$$n_{sm,p,t}^{c,on} \leq n_{sm,p,t}^{c,av} \quad \forall sm \in \mathcal{SM}, p \in \mathcal{P}, t \in \mathcal{T}, \tag{5.38}$$

$$n_{sm,p,t}^{d,on} + n_{sm,p,t}^{+,su,d} \leq n_{sm,p,t}^{d,av} \quad \forall sm \in \mathcal{SM}, p \in \mathcal{P}, t \in \mathcal{T}. \tag{5.39}$$

Logical conditions

The number of online charging or discharging PHS units can be changed by starting up or shutting down a number of units:

$$n^{c,on}_{sm,p,t+1} = n^{c,on}_{sm,p,t} + n^{c,su}_{sm,p,t} - n^{c,sd}_{sm,p,t} \quad \forall sm \in \mathcal{SM}, p \in \mathcal{P}, t \in \mathcal{T}, \qquad (5.40)$$

$$n^{d,on}_{sm,p,t+1} = n^{d,on}_{sm,p,t} + n^{d,su}_{sm,p,t} - n^{d,sd}_{sm,p,t} \quad \forall sm \in \mathcal{SM}, p \in \mathcal{P}, t \in \mathcal{T}. \qquad (5.41)$$

In addition, the discrete nature of the pumps and turbines is reflected by restricting the variables representing a number of units to natural numbers, i.e., integer variables are used:

$$n^{c,av}_{sm,p,t}, n^{c,on}_{sm,p,t}, n^{c,su}_{sm,p,t}, n^{c,sd}_{sm,p,t}, n^{d,av}_{sm,p,t}, n^{d,on}_{sm,p,t}, n^{d,su}_{sm,p,t},$$

$$n^{d,sd}_{sm,p,t}, n^{+,su,d}_{sm,p,t}, n^{+,sd,c}_{sm,p,t} \in \mathbb{Z}^+_0 \quad \forall sm \in \mathcal{SM}, p \in \mathcal{P}, t \in \mathcal{T}. \qquad (5.42)$$

Energy balance and reservoir

Storage technology-types can transfer energy on both the short and the longer term. Since the temporal representation of the model is based on using a limited number representative periods, special attention is needed to consider arbitrage opportunities over longer periods (e.g., months or seasons). To allow arbitraging over longer time frames, energy transfer between different representative periods is required. This implies that within each representative period, the model must allow a net change in the energy content in the reservoir, such that for instance the storage is allowed to be charged during the first representative period and gradually discharged during the second and third representative periods. Recall further that each representative period is assumed to occur a number of times within a single year (represented by parameter W_p, see Chapter 4)[7]. However, assumptions need to be made regarding how the occurrence of a certain representative period is spread over the course of the year. In this work, it is assumed that each representative period p is repeated a number of times equal to its weight W_p, before the subsequent representative period $p+1$ starts (which in turn is repeated a number of times W_{p+1}).

Under these assumptions, the relationship between the energy content at the start of each representative period and the charging and discharging decisions within the corresponding representative periods is expressed as follows:

$$e^f_{s,p+1,t=1} = e^f_{s,p,t=1} + \sum_{t \in \mathcal{T}} \left(W_p \Delta_t (p^c_{s,p,t} \sqrt{\eta_s} - \frac{p^d_{s,p,t}}{\sqrt{\eta_s}}) \right) \quad \forall s \in \mathcal{S}, p \in \mathcal{P}. \quad (5.43)$$

[7] Note further that the charging/discharging pattern is identical within each repetition of a certain representative period, i.e., there is only a single dispatch variable per representative period and time step.

To ensure that within each representative period, the energy content does not exceed its limits, additional constraints are required. Although the charging and discharging pattern is the same for each repetition of the representative period, due to the option of having a net increase/decrease within each representative period, the energy content in the reservoir can increase/decrease as the representative period is repeated. Given that there is either a net increase or a net decrease of the energy content in the reservoir for all repetitions of a single representative period, it can be derived that if the energy content would violate its limits during certain repetitions of the representative period, this would definitively be the case within the first and/or last repetition of the period. Assume for instance that there is a net increase in the energy content over the course of the representative period. In this case, if the upper limit of the energy reservoir would be exceeded, this would definitively be exceeded in the last repetition of the representative period. In addition, if the lower limit would be violated, this would definitively be the case in the first repetition of the representative period. This is visualized in Fig. 5.3. A similar reasoning can be followed when a net decrease in the energy content is assumed.

Thus to make sure that the energy content does not violate its limits, the energy content within the first and the last repetition of the representative period must first be determined:

$$e^f_{s,p,t+1} = e^f_{s,p,t} + \Delta_t(p^c_{s,p,t}\sqrt{\eta_s} - \frac{p^d_{s,p,t}}{\sqrt{\eta_s}}) \quad \forall s \in \mathcal{S}, p \in \mathcal{P}, t \in \mathcal{T} : t \neq \|\mathcal{T}\|, \tag{5.44}$$

$$e^l_{s,p,t=1} = e^f_{s,p,t=1} + \sum_{t\in\mathcal{T}} \Big((W_p - 1)\Delta_t(p^c_{s,p,t}\sqrt{\eta_s} - \frac{p^d_{s,p,t}}{\sqrt{\eta_s}})\Big) \quad \forall s \in \mathcal{S}, p \in \mathcal{P}, \tag{5.45}$$

$$e^l_{s,p,t+1} = e^l_{s,p,t} + \Delta_t(p^c_{s,p,t}\sqrt{\eta_s} - \frac{p^d_{s,p,t}}{\sqrt{\eta_s}}) \quad \forall s \in \mathcal{S}, p \in \mathcal{P}, t \in \mathcal{T} : t \neq \|\mathcal{T}\|. \tag{5.46}$$

Next, the minimum and maximum energy content limits can be enforced for the first and last repetition of each representative period:

$$\begin{aligned} &cap^e_s - \Delta_t p^c_{s,p,t}\sqrt{\eta_s} \geq e^f_{s,p,t} \geq \\ &\Delta_t \frac{p^d_{s,p,t}}{\sqrt{\eta_s}}) + \sum_{r\in\mathcal{R}} (r^{+,d}_{r,s,p,t} T^{DUR}_r) \quad \forall s \in \mathcal{S}, p \in \mathcal{P}, t \in \mathcal{T}, \end{aligned} \tag{5.47}$$

$$\begin{aligned} &cap^e_s - \Delta_t p^c_{s,p,t}\sqrt{\eta_s} \geq e^l_{s,p,t} \geq \\ &\Delta_t \frac{p^d_{s,p,t}}{\sqrt{\eta_s}}) + \sum_{r\in\mathcal{R}} (r^{+,d}_{r,s,p,t} T^{DUR}_r) \quad \forall s \in \mathcal{S}, p \in \mathcal{P}, t \in \mathcal{T}. \end{aligned} \tag{5.48}$$

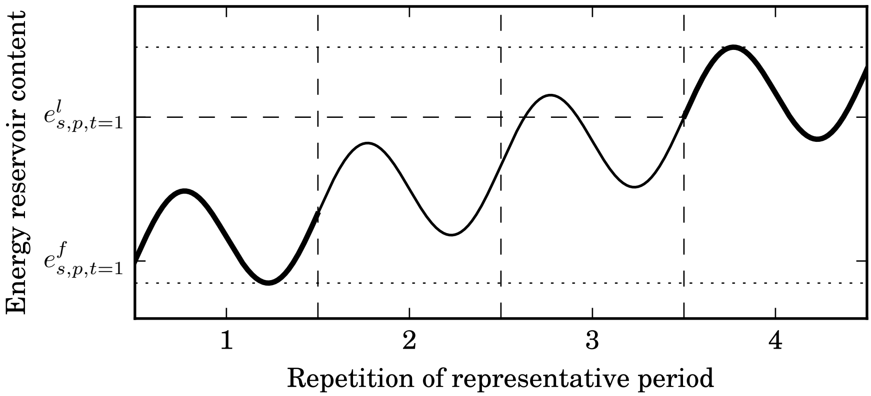


Figure 5.3: Methodology for modeling storage arbitrage opportunities within the representative period and accross different representative periods. In this example, the storage performs some arbitrage within the representative period, but there is also a net increase in the stored energy over the course of the representative period, which can be utilized in subsequent periods, i.e., there is the possibility to arbitrage between representative periods. To ensure that the energy content limits are not exceeded, it is sufficient to guarantee that in the first and the last repitition of the representative period the limits are not exceeded. This is visualized by the dotted lines which indicate the minimum and maximum stored energy level.

Eq. (5.47)-(5.48) also make sure that whenever spinning reserves are procured from storage systems, the energy content limits would not be violated if the procured reserves would need to be activated for a duration T_r^{DUR}.

It must be noted that whenever each representative period is repeated rather frequently (for instance if a low number of representative periods is used and/or the duration of each representative period is short), the assumption of having all repetitions of each representative period directly after each other will likely overly restrict the ability to arbitrage over longer time frames. This because, due to the high number of repetitions, a small net increase/decrease of the energy content over the course of a single repetition of a representative period can already lead to a high net increase/decrease of the energy content over all repetitions of this representative period. As a consequence, the energy reservoir limits can quickly become binding, thereby restricting the net increase/decrease within each representative period to small amounts. Further research is required to analyze and improve the modeling of longer term storage when using representative periods.

Charging/discharging level constraints

For BESS, the charging/discharging level is constrained by the available capacity and the procured upward reserves. Note that the upward reserves that can be provided while charging correspond to a decrease of the charging power.

$$p^c_{ss,p,t} \leq cap^{av}_{ss} \quad \forall ss \in \mathcal{SS}, p \in \mathcal{P}, t \in \mathcal{T}, \tag{5.49}$$

$$p^d_{ss,p,t} + \sum_{r\in\mathcal{R}} r^{+,d}_{r,ss,p,t} \leq cap^{av}_{ss} \quad \forall ss \in \mathcal{SS}, p \in \mathcal{P}, t \in \mathcal{T}. \tag{5.50}$$

$$p^c_{ss,p,t} \geq \sum_{r\in\mathcal{R}} r^{+,c}_{ss,p,t} \quad \forall ss \in \mathcal{SS}, p \in \mathcal{P}, t \in \mathcal{T}. \tag{5.51}$$

For PHS, the maximum charging/discharging power is dependent on the number of online units:

$$p^c_{sm,p,t} \leq n^{c,on}_{sm,p,t}\overline{P}_{sm} \quad \forall sm \in \mathcal{SM}, p \in \mathcal{P}, t \in \mathcal{T}, \tag{5.52}$$

$$p^d_{sm,p,t} + \sum_{r\in\mathcal{R}} r^{+,spin,d}_{r,sm,p,t} \leq n^{d,on}_{sm,p,t}\overline{P}_{sm} \quad \forall sm \in \mathcal{SM}, p \in \mathcal{P}, t \in \mathcal{T}. \tag{5.53}$$

Similar to the thermal power plants, both in pumping and turbining mode, MSOP restrictions must be respected:

$$p^c_{sm,p,t} \geq n^{c,on}_{sm,p,t}\underline{P}^C_{sm} + \sum_{r\in\mathcal{R}} r^{+,spin,c}_{r,sm,p,t} \quad \forall sm \in \mathcal{SM}, p \in \mathcal{P}, t \in \mathcal{T}, \tag{5.54}$$

$$p^d_{sm,p,t} \geq n^{d,on}_{sm,p,t}\underline{P}^D_{sm} \quad \forall sm \in \mathcal{SM}, p \in \mathcal{P}, t \in \mathcal{T}, \tag{5.55}$$

Ramping constraints

For BESS, no ramping constraints are considered. In contrast, PHS face upward and downward ramping constraints, both while charging and while discharging:

$$\begin{aligned} p^c_{sm,p,t+1} - p^c_{sm,p,t} + \sum_{r\in\mathcal{R}} r^{+,spin,c}_{r,sm,p,t} &\leq (n^{c,on}_{sm,p,t} - n^{c,sd}_{sm,p,t})\overline{P}_{sm}\frac{R_{sm}}{100}\Delta_t \\ &- n^{c,sd}_{sm,p,t}\underline{P}^C_{sm} + n^{c,su}_{sm,p,t}\overline{P}_{sm} \quad \forall sm \in \mathcal{SM}, p \in \mathcal{P}, t \in \mathcal{T}, \end{aligned} \tag{5.56}$$

$$p^d_{sm,p,t+1} - p^d_{sm,p,t} + \sum_{r\in\mathcal{R}} r^{+,spin,d}_{sm,p,t+1} \leq (n^{d,on}_{sm,p,t} - n^{d,sd}_{sm,p,t})\overline{P}_{sm}\frac{R_{sm}}{100}\Delta_t$$

$$- n^{d,sd}_{sm,p,t}\underline{P}^{D}_{sm} + n^{d,su}_{sm,p,t}\overline{P}_{sm} \quad \forall sm \in \mathcal{SM}, p \in \mathcal{P}, t \in \mathcal{T}, \tag{5.57}$$

$$p^{c}_{sm,p,t} - p^{c}_{sm,p,t+1} + \sum_{r\in\mathcal{R}} r^{+,spin,c}_{sm,p,t+1} \leq (n^{c,on}_{sm,p,t} - n^{c,sd}_{sm,p,t})\overline{P}_{sm}\frac{R_{sm}}{100}\Delta_t$$

$$+ n^{c,sd}_{sm,p,t}\overline{P}_{sm} - n^{c,su}_{sm,p,t}\underline{P}^{C}_{sm} \quad \forall sm \in \mathcal{SM}, p \in \mathcal{P}, t \in \mathcal{T}, \tag{5.58}$$

$$p^{d}_{sm,p,t} - p^{d}_{sm,p,t+1} + \sum_{r\in\mathcal{R}} r^{+,spin,d}_{r,sm,p,t} \leq (n^{d,on}_{sm,p,t} - n^{d,sd}_{sm,p,t})\overline{P}_{sm}\frac{R_{sm}}{100}\Delta_t$$

$$+ n^{d,sd}_{sm,p,t}\overline{P}_{sm} - n^{d,su}_{sm,p,t}\underline{P}^{D}_{sm} \quad \forall sm \in \mathcal{SM}, p \in \mathcal{P}, t \in \mathcal{T}. \tag{5.59}$$

Provision of reserves

Upward reserves by storage technology-types can be provided by increasing the discharging power or decreasing the scheduled charging power:

$$r^{+}_{r,s,p,t} = r^{+,c}_{r,s,p,t} + r^{+,d}_{r,s,p,t} \quad \forall r \in \mathcal{R}, s \in \mathcal{S}, p \in \mathcal{P}, t \in \mathcal{T} \tag{5.60}$$

The provision of reserves by BESS is restricted by the energy content in the reservoir (Eq. (5.47)-(5.48)), the available head room while discharging (Eq. (5.50)) and the amount of scheduled charging power (Eq. (5.51)).

For PHS, the procurement of reserves by increasing the level of discharging is also restricted by the energy content in the reservoir (Eq. (5.47)-(5.48)). To consider technical constraints for PHS, the provision of upward reserves while charging/discharging is divided into spinning and non-spinning reserves:

$$r^{+,c}_{r,sm,p,t} = r^{+,spin,c}_{r,sm,p,t} + r^{+,ns,c}_{r,sm,p,t} \quad \forall r \in \mathcal{R}, sm \in \mathcal{SM}, p \in \mathcal{P}, t \in \mathcal{T}, \tag{5.61}$$

$$r^{+,d}_{r,sm,p,t} = r^{+,spin,d}_{r,sm,p,t} + r^{+,ns,d}_{r,sm,p,t} \quad \forall r \in \mathcal{R}, sm \in \mathcal{SM}, p \in \mathcal{P}, t \in \mathcal{T}. \tag{5.62}$$

The provision of spinning reserves is restricted by the available head room while discharging (see Eq. (5.53)), and the minimum stable operating point (MSOP) while charging (see Eq. (5.54)). In addition, ramping constraints need to be considered (upward ramping while discharging and downward ramping while charging):

$$\sum_{r\in\mathcal{R}:T^{ACT}_{r}\leq T^{ACT}_{r'}} r^{+,spin,d}_{r,sm,p,t} \leq (n^{d,on}_{sm,p,t} - n^{d,sd}_{sm,p,t})\overline{P}_{sm}\frac{R_{sm}}{100}T^{ACT}_{r'}$$

$$\forall r' \in \mathcal{R}, sm \in \mathcal{SM}, p \in \mathcal{P}, t \in \mathcal{T}. \tag{5.63}$$

$$\sum_{r \in \mathcal{R}: T_r^{ACT} \leq T_{r'}^{ACT}} r_{r,sm,p,t}^{+,spin,c} \leq (n_{sm,p,t}^{c,on} - n_{sm,p,t}^{c,sd} - n_{sm,p,t}^{+,sd,c})$$

$$\overline{P}_{sm} \frac{R_{sm}}{100} T_{r'}^{ACT} \quad \forall r' \in \mathcal{R}, sm \in \mathcal{SM}, p \in \mathcal{P}, t \in \mathcal{T}. \tag{5.64}$$

Finally, also the reserves provided by starting up additional discharging units, or shutting down charging units need to be restricted:

$$\sum_{r \in \mathcal{R}: T_r^{ACT} < SUT_{sm}^{D}} r_{r,sm,p,t}^{+,ns,d} = 0 \quad \forall sm \in \mathcal{SM}, p \in \mathcal{P}, t \in \mathcal{T}, \tag{5.65}$$

$$\sum_{r \in \mathcal{R}: T_r^{ACT} < SDT_{sm}^{C}} r_{r,sm,p,t}^{+,ns,c} = 0 \quad \forall sm \in \mathcal{SM}, p \in \mathcal{P}, t \in \mathcal{T}, \tag{5.66}$$

$$\sum_{r \in \mathcal{R}: T_r^{ACT} \geq SUT_{sm}^{D}} r_{r,sm,p,t}^{+,ns,d} \leq n_{sm,p,t}^{+,su,d} \overline{P}_{sm} \quad \forall sm \in \mathcal{SM}, p \in \mathcal{P}, t \in \mathcal{T} \tag{5.67}$$

$$\sum_{r \in \mathcal{R}: T_r^{ACT} \geq SDT_{sm}^{C}} r_{r,sm,p,t}^{+,ns,c} \leq n_{sm,p,t}^{+,sd,c} \underline{P}_{sm}^{C} \quad \forall sm \in \mathcal{SM}, p \in \mathcal{P}, t \in \mathcal{T} \tag{5.68}$$

Due to the fact that spinning reserves can be provided by reducing the pumping (charging) level down to the MSOP, non-spinning reserves are restricted to the MSOP.

5.3.3 Validation of the clustered UC formulation

In a paper not in full included within this thesis, we have shown that the results provided by a CUC model can, in some specific cases, deviate to a small extent from those of a traditional UC formulation (even if only identical plants are grouped within a cluster) [168]. These deviations are shown to occur whenever the generation output of units directly after a start-up or immediately before a shut-down is restricted, or whenever a non-linear relationship between the generation output and the fuel consumption is considered within the operating range of the unit. These errors are shown to originate from the fact that the CUC formulation does not keep track of the generation level of individual units. As the flexibility that can be provided by a group of power plants does not only depend on the aggregate generation level of all plants within the group, but also on how this generation level is distributed among different units, errors can arise.

The errors induced by the clustered formulation have been quantified by comparing the results of the CUC model applied to the Central Western European electricity system to the results provided by a traditional UC model which uses binary commitment variables to schedule the commitment status of individual plants. For the performed simulations, the differences in projected operational cost did not exceed 0.06%. We have therefore concluded that the CUC model approximates the traditional UC model with very high accuracy. In terms of computation complexity, however, the CUC formulation was shown to be a factor of 80-800 faster than the traditional UC model. For a detailed description of this work, we refer to [168].

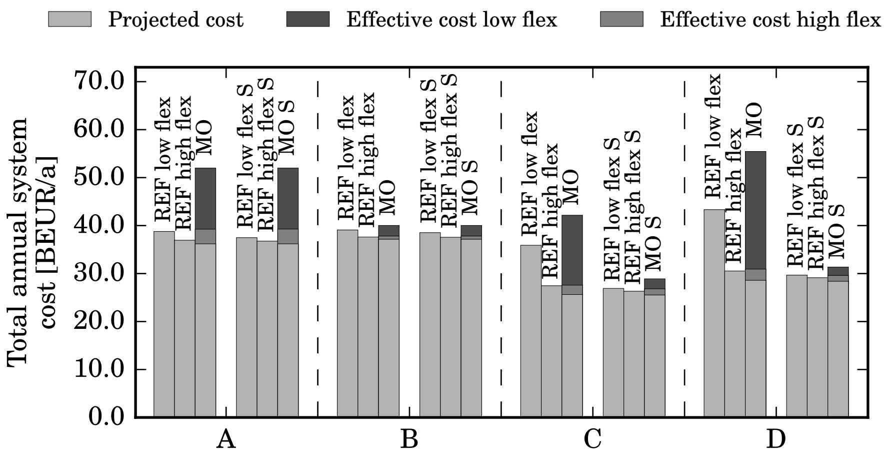
5.4 Results and discussion

5.4.1 Relevance of incorporating technical constraints in planning models

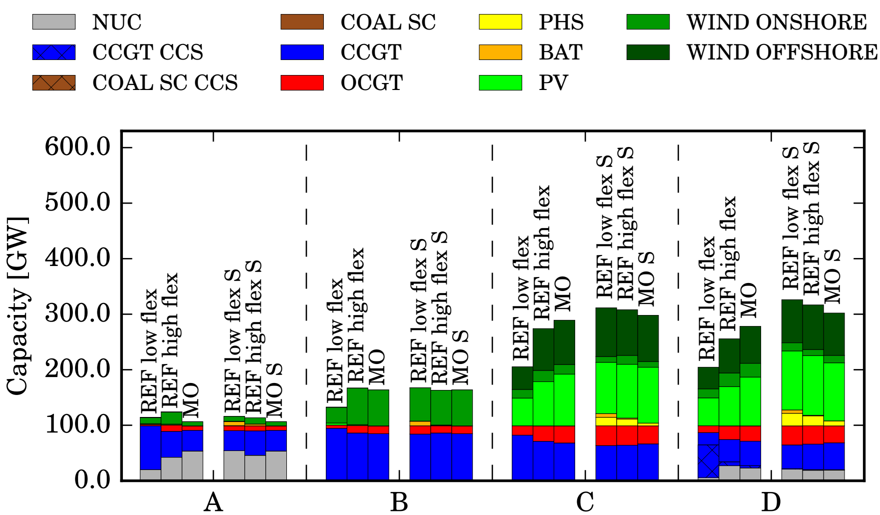
Impact of neglecting technical constraints in planning models

Fig. 5.4a displays the projected total annual system costs for all scenarios and cases in the simulations where all technical constraints are included (REF) and the simulations where all technical constraints are omitted (MO). Additionally, this figure displays the total system cost whenever the operational cost of the MO simulation is reevaluated by fixing the installed capacities and solving the CUC problem with all technical constraints included, i.e., the effective total system cost. This reevaluation is done using both the stringent and the optimistic assumptions regarding the flexibility of thermal power plants. Additionally, Fig. 5.4b presents the capacity mix resulting from the different cases and scenarios considered, both with and without including technical constraints. The different scenarios and cases were listed above in Tab. 5.2-5.3.

From Fig. 5.4a, it can be observed that for the majority of cases and scenarios considered, incorporating detailed technical constraints has only a limited impact on the projections of the total system cost (light grey bars). Whenever scenarios have a low penetration of IRES, thermal power plants are highly flexible (high flex) or other sources of flexibility are available at a reasonable cost, the cost projection errors are in the range of 1.5-7%. As can be expected, these cost differences tend to be bigger whenever plants are less flexible, other sources of flexibility are not available and the share of nuclear and IRES generation is higher. A few exceptions exist for which neglecting technical constraints results in a significant underestimation of the projected total system cost. This is the case whenever there is a high share of renewables (i.e., scenario C and D), thermal power plants are limitedly flexible (low flex) ánd other sources of flexibility are not available.



(a)



(b)

Figure 5.4: Impact of neglecting technical plant and system-level constraints on (a) the projected and effective total system cost and (b) the capacity mix. The scenarios A through D are defined in Tab. 5.2. The terms 'low flex', 'low flex S', 'high flex' and 'high flex S' refer to the different cases, as presented in Tab. 5.3.

By comparing the effective total system costs in Fig. 5.4a, it can be observed that not incorporating technical constraints in the planning model does result in suboptimalities[8]. However, for the majority of the cases and scenarios considered, these suboptimalities are relatively small. Again, the impact of not incorporating technical constraints in the planning model increases whenever plants are less flexible, other sources of flexibility are not available and the share of IRES is higher. Only when stringent assumptions are taken regarding the flexibility of thermal power plants and storage technology-types are not available (or not invested in without the incorporation of technical constraints), the suboptimalities do become significant. The higher reevaluated costs are mainly the result of higher fuel costs, emission costs and fewer IRES support gains. One exception is scenario A, where the suboptimality is very high in the cases with inflexible thermal power plants, despite the fact that the penetration of IRES is low. This results from the high share of nuclear capacity which, due to the stringent ramping requirements, can hardly contribute to the provision of spinning reserves. In combination with the high reserve requirements, this leads to a frequent shedding of reserves which is strongly penalized. In the scenarios and cases where there is a large suboptimality, this could likely be significantly reduced if the capacity mix could be slightly adapted by adding some additional flexibility (e.g., BESS), or by making use of all available flexibility (e.g., the provision of upward reserves by IRES).

Fig. 5.4b shows that for the majority of the scenarios and cases considered, also the impact of neglecting technical constraints on the capacity mix is rather small. A first exception is whenever thermal power plants are limitedly flexible and no other sources of flexibility are available (low flex case). In this case, neglecting technical constraints turns out to be significant for all scenarios. In contrast, whenever thermal power plants are highly flexible or other sources of flexibility are considered, differences in investments in both thermal generators and IRES becomes moderate to low. A second exception relates to investments in storage technology-types, and especially BESS. Here, it can be observed that whenever technical constraints are omitted, no or few investments in BESS and PHS can be observed, whereas significant investments in storage technology-types can be observed whenever technical constraints are incorporated.

In terms of investments in thermal plants and IRES, it is more difficult to observe clear trends regarding the impact of not considering detailed technical constraints. In general, we can observe that not incorporating these constraints results in a bias towards a higher penetration of IRES and baseload technology-types at the expense of fewer flexible mid or peak load power plants. However, since a higher penetration of IRES reduces the number of operating hours

[8] Recall that when technical constraints are considered in the planning model (REF), the projected cost corresponds to the effective cost.

of baseload technology-types, it can be the case that not including technical constraints results in an increase of the penetration of IRES which comes at the expense of a reduction in the installed capacity of baseload technology-types (e.g., in scenario C without storage, fewer CCGTs are installed in the MO simulation due to the fact that more IRES are installed in the MO simulation) or vice versa (e.g., in scenario A without storage, more investments in nuclear power plants can be observed in the MO simulation at the expense of fewer investments in wind turbines.).

Pitfalls for incorporating technical constraints

From Fig. 5.4, a big difference between the projected system costs and capacity mixes in the reference simulations can be observed depending on whether stringent or more optimistic assumptions are taken regarding the flexibility of thermal power plants, and depending on whether or not other sources of flexibility, such as electricity storage technology-types are considered. This suggests that care should be taken when incorporating technical constraints in planning models. Particularly when modeling scenarios with a high penetration of IRES, and when assuming rather inflexible power plants, the value of flexibility can become extremely high. This is also apparent from the significant difference in the projected total annual system cost between the low flex reference case and the other reference cases in scenario C and D. These difference indicate that every source of flexibility, be it more flexible thermal power plants, storage technology-types or other sources of flexibility, has the potential to reduce costs significantly (even if this source of flexibility would be highly expensive). For this reason, assuming that no source of flexibility will be found can be considered highly unrealistic. To illustrate this point, Tab. 5.6 presents the annual total system costs in the low flex case with and without storage for scenario C and D. Additionally, this table presents the total system costs one would obtain whenever the solution of the system with storage is taken, but the investment cost of all storage technology-types are multiplied by a factor of 3 (indicated by low flex Sx3)[9]. This table shows that even when storage technology-types would be three times more expensive, the total system costs would be significantly lower than those projected by a model in which storage technology-types would not be considered at all. Similarly, in such a flexibility-constrained system, it can be expected that thermal power plants would be designed to offer more flexibility [169], or simply operated more flexibly at the expense of higher wear and tear costs[10]. We therefore conclude that it is imperative to account for

[9] Note that this forms an upper bound of the optimal solution when storage technology-types would be this expensive.

[10] As discussed in [6], cycling parameters can reflect both hard technical constraints but also more cost-related constraints.

other sources of flexibility and/or the ability to increase the flexibility of thermal power plants whenever incorporating detailed technical constraints in planning models. If one does not account for other sources of flexibility in planning models, and assumes inflexible thermal power plants, one can introduce errors both in terms of projecting the total system cost and deriving the optimal capacity mix which can be significantly higher than the errors one would obtain if technical constraints would be completely omitted.

Scenario	low flex S	low flex Sx3	low flex
C	26.9	28.6	33.4
D	29.7	31.9	43.3

Table 5.6: Overview of the total annual system costs projections in the low flex case with storage, highly expensive storage and without storage. All costs are expressed in billion euros per year.

The inclusion of different flexibility sources also reduces the impact of the choice of cycling characteristics of thermal power plants. Nevertheless, even if storage technology-types are considered, the differences between the high flex case and the low flex case remain of the same order of magnitude as the difference between the high flex and the MO case, both in terms of projected system cost (see Fig. 5.4a) and in terms of investments in storage technology-types (see Fig. 5.4b). Since storage technology-types and other sources of flexibility compete directly with thermal generators for the provision of flexibility, the choice of cycling characteristics of thermal power plants is shown to have a significant impact on the investments in storage technology-types (and BESS in particular). Modelers should thus be aware of the importance of this choice. Wherever possible, we recommend to actively consider the sensitivity of the results to the choice of cycling parameters.

Conclusion and recommendations

For most scenarios and cases, the impact of neglecting technical constraints in planning models on the projected system costs and the capacity mix is limited. An exception needs to be made for investments in storage technology-types, which were shown to be strongly influenced by incorporating technical constraints (as well as the cycling characteristics assumed for thermal power plants). Although we did not explicitly look at other sources of flexibility, this can likely be generalized to other dedicated flexibility providers.

When incorporating technical constraints in planning models, care must be taken that the model is not overly conservative. This can be the case if thermal power plants are assumed to be rather inflexible and no other sources of flexibility are considered. In such models, the projections of the total system cost, as well as the challenge of integrating large shares of IRES can be strongly overestimated. To avoid this issue, we recommend considering multiple sources of flexibility whenever incorporating technical constraints in planning models.

5.4.2 Impact of individual system or plant-level constraints

In this section, we analyze to what extent and how individual technical constraints impact the results of a long-term planning model. This will provide valuable insights and information which will be used in Section 5.4.4 for developing an accurate and computationally lean approximation of the clustered unit commitment (CUC) problem which can be integrated in large-scale planning models.

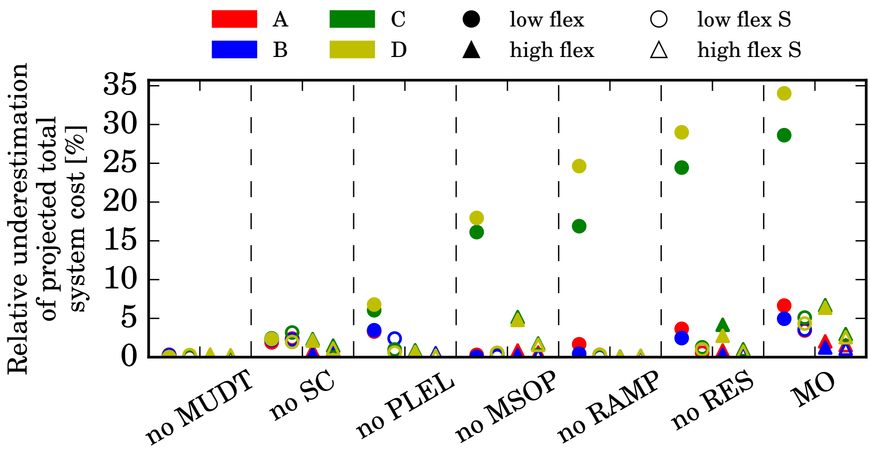
Fig. 5.5a-5.5b display for all considered cases and scenarios the errors in the projected total system cost and the effective total system cost[11] when specific technical constraints are not incorporated in the planning model. In addition, Fig. 5.6 displays the impact of neglecting individual constraints on the capacity mix for the different cases and scenarios.

In general, we can observe that reserve requirements have the biggest impact on the results (see Fig. 5.5a-5.5b, "no RES"). Moreover, ramping rate restrictions, minimum stable operating point (MSOP) constraints as well as part-load efficiency losses (PLEL) can have a considerable impact. However, the importance of these constraints is strongly determined by the considered scenario, the assumed cycling characteristics as well as the availability of storage technology-types. In contrast, the impact of start-up costs (SC) is moderate to low across all considered cases and scenarios, whereas minimum up and down time (MUDT) constraints have a negligible impact for all considered cases and scenarios. Below, the impact of each individual constraint is analyzed in detail.

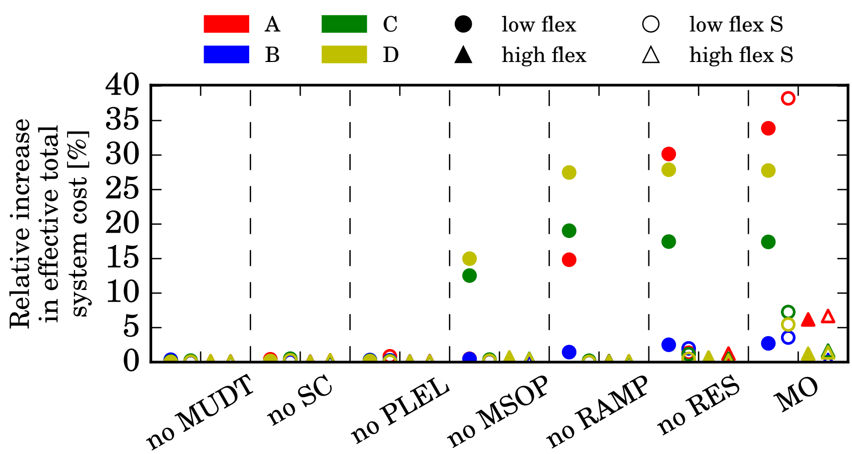
Reserve constraints

We consider here the provision of upward reserves on different time frames. As specified in Tab. 5.5, the majority of the considered reserves needs to come

[11] Recall from Section 5.2.1 that the effective total system cost corresponds to the total system cost when the operational costs are reevaluated using a CUC model which incorporates all technical constraints.



(a)



(b)

Figure 5.5: (a) Relative underestimation of the projection of the total system costs for the different scenarios and cases when specific technical constraints are not considered. (b) Relative increase in total system costs when specific technical constraints are not considered during the investment planning. The operational costs are reevaluated using a CUC model which considers all technical constraints. The technical constraints considered separately are the minimum up and down time (MUDT) requirements, start-up costs (SC), part-load efficiency losses (PLEL), minimum stable operating point (MSOP) restrictions, ramping limits (RAMP) and reserve requirements (RES). The impact of not incorporating any technical constraints is referred to as merit order (MO).

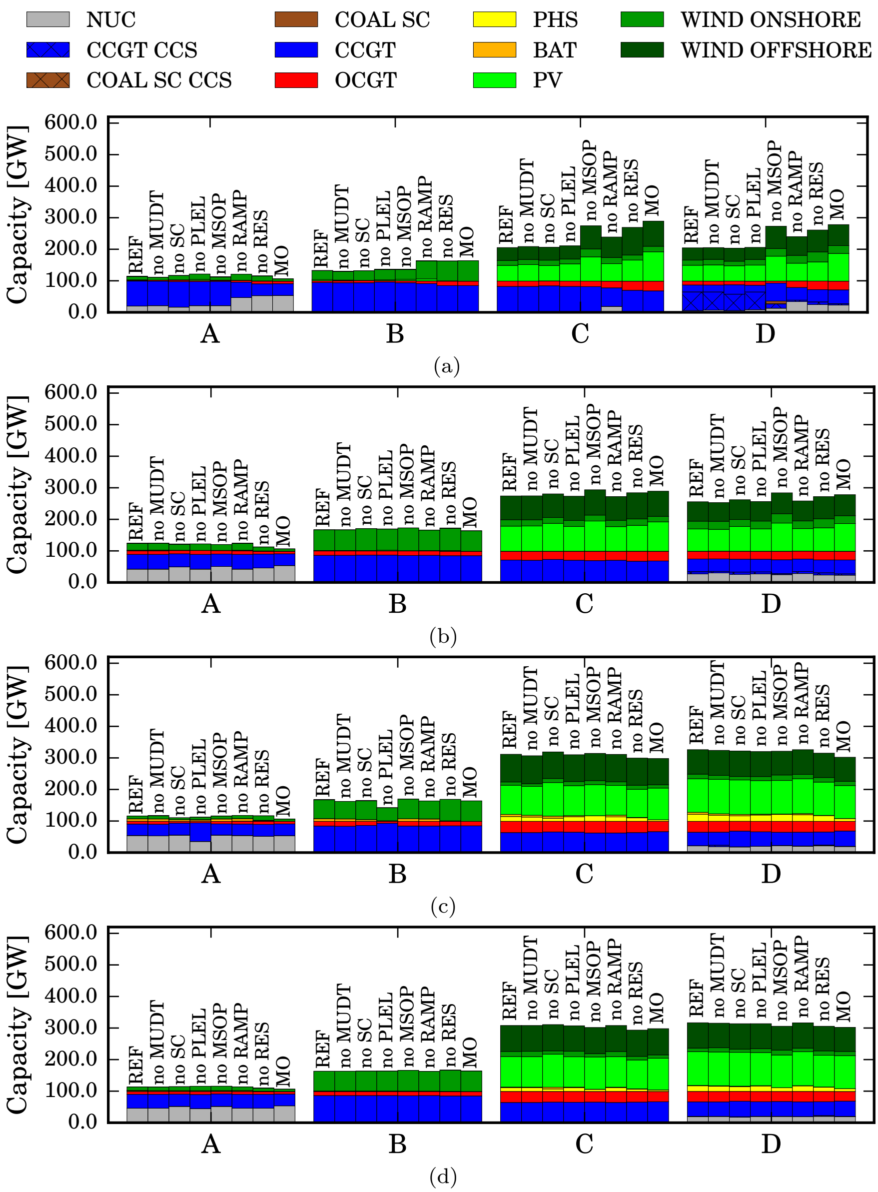


Figure 5.6: Capacity mix for the different scenarios when individual constraints are not considered in the in the low flex case (a), the high flex case (b), the low flex S case (c) and the high flex S case (d).

from spinning reserves. In addition, due to the assumptions taken regarding the start-up times of thermal power plants and the required activation times for reserves, thermal power plants cannot provide fast-starting frequency regulation reserves (FRR) and spinning contigency reserves (SCR) reserves. In combination with the 100% spinning reserve requirement for variable renewable forecast error reserves (VRFER), this means that thermal power plants cannot provide fast-starting reserves for any of the considered reserve types. As the name states, the provision of spinning reserves is restricted to spinning, i.e., online, units. One exception is the provision of reserves by battery energy storage systems (BESS), which are considered to be equivalent to "spinning" since BESS can start charging or discharging sufficiently fast for the provision of reserves for all reserve types.

The results presented in Fig. 5.5 and Fig. 5.6 clearly show that the impact of incorporating reserve requirements becomes higher whenever there is a higher penetration of IRES technology-types (i.e., in scenarios C and D). This is due to multiple reasons. First, an increasing penetration of IRES increases the need for reserves to deal with possible deviations from the forecasted conditions. Second, with an increasing instantaneous generation of IRES, the number of thermal generators which need to be online to generate electricity is reduced. Therefore, a higher volume of reserves needs to be provided by fewer units. In moments of high IRES generation, a minimum number of spinning units needs to remain online in order to provide the reserve requirements. Since these units are bound to generate above a minimum threshold, i.e., the MSOP, curtailment of IRES generation will be required before the entire demand is served by IRES[12]. At higher penetration levels of IRES, this need to curtail will occur more frequently.

Whenever generators are assumed to have limited flexibility and storage technology-types or other sources of flexibility are not available or cannot contribute to the provision of reserves (low flex case), incorporating reserve requirements can have a very high impact on both the investments and the total system costs. By comparing the capacity mix in the "no RES" simulations to the capacity mix in the reference simulations in Fig. 5.6a, we can observe that incorporating reserve requirements can cause a shift away from less flexible nuclear units to more flexible gas-fired plants. In addition, introducing reserve requirements strongly reduces the value of investments in IRES, particularly at higher penetration levels. As a result, fewer investments in IRES can be observed in Fig. 5.6a whenever reserve constraints are considered.

The impact of these reserve requirements is strongly reduced whenever thermal generators are more flexible (see the triangles versus the circles in Fig. 5.5). The

[12] It might be the case that a minimum level of electricity needs to be generated by spinning (thermal) generators in any case to have sufficient inertia to ensure the stability of the system. The issue of system inertia deserves further attention but is not considered here.

provision of upward reserves by spinning generators is first of all restricted by the available head room, i.e., the margin between the rated capacity and the current power output (see Eq. (5.22)). Spinning reserve constraints thus force units to operate below their rated capacity in order to ensure sufficient head room. In addition, the amount of spinning reserves that can be provided is restricted by the ability of an online unit to ramp up its power output in the required time frame (see Eq. (5.30)). As such, spinning reserve requirements impose that a sufficiently high number of sufficiently flexible units are spinning at all times. As will be discussed in more detail below, particularly the ramping capabilities and the minimum operating point play a key role here. As the ramping capabilities increase and the minimum operating point decreases, thermal units can provide more reserves per unit of electricity generated. As a result, in periods of high wind and/or solar generation, IRES can provide a much higher fraction of the demand which strongly reduces the fuel costs. With more flexible thermal generators (high flex case), we can observe from Fig. 5.6b that incorporating reserve requirements still increases total system costs and remains to cause a shift towards less IRES and less flexible baseload plants. However, the impact of neglecting reserve requirements in this case is small.

For the provision of reserves, storage systems have the inherent advantage that they can provide upward reserves without having to be in the process of generating electricity. BESS are sufficiently fast to provide reserves without having to be in the process of charging or discharging. While this is not necessarily the case for PHS systems, PHS can still provide upward reserves while charging. For instance, when charging at rated capacity, upward reserves can be provided by reducing the charging power. Particularly in systems with a high penetration of IRES, this offers the advantage that curtailment of IRES and the need to generate electricity using thermal generators can (to some extent) be avoided. This is in line with the findings in [155].

Fig. 5.5a shows that when storage technology-types can provide reserves, the impact of reserves on the projections of the total system costs becomes almost negligible (hollow circles and triangles versus full circles and triangles). More specifically, the relative underestimation of the total system cost is systematically below 1.5% for the cases with storage (see the hollow circles and triangles for the "no RES" simulations in Fig. 5.5a). Nevertheless, by comparing in Fig. 5.6c-5.6d the capacity mix in the reference simulation to the capacity mix in the simulation where reserve constraints are not incorporated, we observe that reserve constraints form a determining factor for investments in storage technology-types in general and BESS in particular. However, even when one incorporates reserve constraints, the investments in storage technology-types are strongly dependent on the flexibility of thermal power plants, as they are in direct competition with storage technology-types for the provision of reserves.

Especially for the provision of reserves with small activation times, the assumed flexibility of thermal power plants can have a big impact. In the low flex S case, storage technology-types provide over 95% of both the FRR and SCR reserves in scenario C and D, whereas in the high flex S case, this drops to slightly above 65%). Whenever storage technology-types can provide reserves, reserve constraints are shown to have a minor impact on investments in both IRES and thermal generators.

Ramping constraints

Ramping-rate restrictions of dispatchable plants limit both the ability to change power output to deal with anticipated variations of the residual load (Eq. (5.23)-(5.24)), and the ability to respond to contingencies or forecast errors (Eq. (5.30)).

A first observation is that in our simulations, the ramping constraints for load following were not binding in any of the considered scenarios[13]. It must be noted that we have employed an hourly resolution. When a more refined resolution would be used, ramping-rate restrictions might become binding if stringent ramping rates are used. However, in recent work of Deane et al.[170], it is shown that even at a 5 minute resolution, ramping-rate restrictions for load-following have only a minor impact on the results. This implies that the impact of ramping-rate restrictions is entirely related to the resulting limitations for the provision of spinning reserves. This can also be seen from Fig. 5.7 which shows the impact of the different constraints when reserves are not considered (i.e., whenever the model which does not incorporate reserve requirements serves as the reference model). Here it can be seen that ramping restrictions do not have a considerable impact on the results whenever reserves are not considered.

For the provision of spinning reserves, ramping restrictions can have a significant impact. However, the impact is strongly dependent on the assumed cycling characteristics.

In the low flex case, nuclear power plants can ramp a mere 2.5% of their committed capacity on the time frame corresponding to the SCR reserves. For CCGTs and open cycle gas turbines (OCGTs), this increases to 8.3%[14]. As a result, these ramping-rate restrictions are frequently binding whenever there is a high demand for the fast reserve categories and few units are online. This happens mainly whenever both demand and IRES generation is high. During these periods, a high number of units is required to remain online for providing

[13]Given the adopted ramp rates (see Tab. 5.4, the ramping capability of nuclear and CCGT units are respectively, 15% and 50% of the nominal capacity within an interval of an hour in the low flex case.

[14]See the adopted ramp rates in Tab. 5.4 and the ramping constraint (Eq. (5.30)).

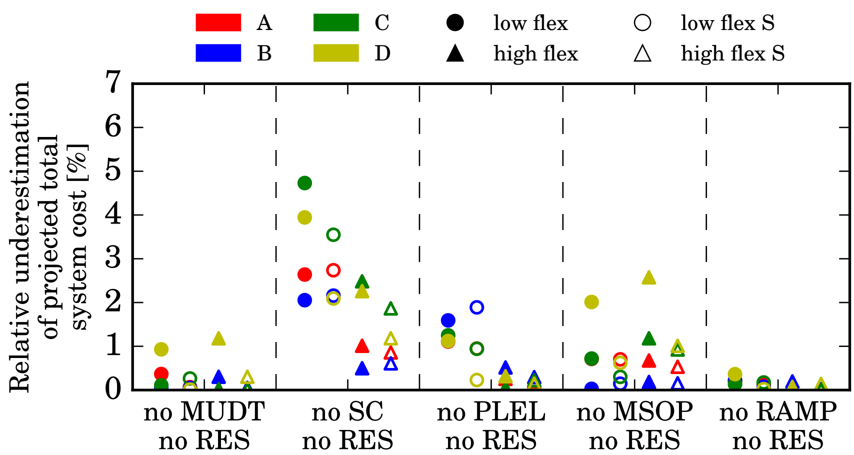


Figure 5.7: Relative underestimation of the projection of the total system costs for the different scenarios and cases when both reserve requirements and specific technical constraints are not considered relative to the run in which no reserve requirements are incorporated.

sufficient ramping capability. Due to the MSOP, a high number of online units implies a significant amount of power generation. To avoid curtailment of IRES as much as possible, thermal units operate in or close to their minimum operating point in these periods. To illustrate this, Tab. 5.7 presents the amount of curtailment and the average operating point of CCGTs in scenario C in the "no RAMP" simulation, and in the reevaluated run (i.e., with the same capacity mix as the one in the "no RAMP" simulation, but all technical constraints incorporated). Here, it can be clearly observed that including the ramping-rate restrictions for the provision of fast reserves forces more thermal generators to be online. To avoid curtailment as much as possible, these units are operated at a lower operating point. Nevertheless, the higher number of spinning units necessitates significant curtailment of IRES generation. By comparing the capacity mix in the reference case to the capacity mix in the simulations in which ramping-rate restrictions are not incorporated in Fig. 5.6a, significantly higher investments in IRES and less flexible baseload technology-types are observed whenever ramping-rate restrictions are not accounted for.

In the high flex cases, nuclear power plants can provide 50% of their committed capacity on the time frame corresponding to the SCR reserves. In addition, CCGTs and OCGTs can ramp up to their rated capacity. As a result, the ramping-rate constraints are rarely binding (and then only for nuclear plants in

	no RAMP	no RAMP reevaluated
Average operating point CCGT [$\%P_{nom}$]	72.4	57.6
Curtailment [%]	7.2	28.2

Table 5.7: Curtailment and generation-weighted average operating point of CCGTs in the simulation of scenario C in the low flex case where ramping restrictions are omitted.

very few instances), and therefore have a negligible impact on the results, as is observed in Fig. 5.5a, Fig. 5.6b and Fig. 5.6d.

Whenever storage technology-types can contribute to the provision of reserves, the ramping-rate restrictions have a minor impact on investments (see Fig. 5.6c-5.6d). This is since storage technology-types provide over 95% of both the FRR and SCR reserves in scenario C and D in the low flex case.

Minimum stable operating point constraints

The minimum stable operating point (MSOP) constraint enforces that if a unit is online, it has to generate electricity at least at a certain power level (Eq. (5.21)). As discussed in the previous sections, the MSOP has a significant impact on the provision of reserves as it establishes a link between the required head room and/or ramping capabilities on the one hand, and the minimum power generation on the other hand. Without MSOP constraints, a high number of units can be committed to ensure sufficient head room and ramping capability without having to generate any electricity using these units, i.e., these units can spin at an operating point where no electricity is generated[15]. As such, the need for IRES curtailment can be strongly reduced. In addition, reducing the operating point can avoid the need to temporarily shut units down, thereby avoiding start-up costs. However, due to the part-load efficiency losses, there is a cost attached to having units operating in part-load, even if these units are idling (i.e., no electricity is generated).

As can be observed from Fig. 5.7, MSOP constraints do not significantly impact results whenever reserve constraints are not considered[16].

[15] It must be noted that it does not make sense to base the ramping capability of thermal generators on the committed capacity when no MSOP constraints are included. In this case, the current power output would be a better indicator of the ramping capability.

[16] In smaller power systems such as island systems, the discrete nature of individual power plants will gain in importance, and hence also the MSOP constraints. However, the focus here is on large, interconnected power systems.

In the low flex case, accounting for MSOP constraints in combination with reserve constraints reduces the amount of investments in IRES as the MSOP constraints induce the need for curtailment. For example, it can be observed that when the minimum operating point constraint is omitted, the operating point of CCGTs is below the MSOP in over 60% of the time steps in scenario C. Due to this reduction in the effective operating point, a slight shift towards technology-types with fewer part-load efficiency losses is observed when minimum operating point constraints are not considered.

In the high flex case, ramping constraints are not binding and it is mainly the ability to circumvent the head-room restrictions which impact the results. These head-room restrictions are mainly binding whenever there are high shares of IRES. Again, not incorporating the minimum stable operating point constraints therefore results in an increase in investments in IRES.

If storage technology-types can provide reserves, the provision of reserves becomes less costly in general. Therefore, also the impact of not incorporating the MSOP constraints has a lower impact on the projections of the total system costs (see hollow circles and triangles versus full circles and triangles for the simulations without MSOP constraints in Fig. 5.5a). However, as neglecting MSOP constraints makes the provision of reserves by thermal generators (and PHSs) less expensive, not incorporating these constraints can be seen to cause a bias towards less investments in storage in general, and BESS in particular. This can be seen by comparing the investments in storage technology-types in the reference simulation and the simulation which does not consider MSOP restrictions in Fig. 5.6c-5.6d.

Part-load efficiency losses

Part-load efficiency losses (PLEL) can have a significant impact on the projection of total system costs. However, this is only the case whenever reserve requirements force the plants to operate in part-load (see the difference between Fig. 5.5a and Fig. 5.7 for the impact of not including PLEL). The operation in part-load is needed to have sufficient head room to provide upward reserves in any case (at least whenever storage technology-types cannot provide reserves), but becomes more pronounced whenever the combination of high penetrations of IRES and stringent ramping-rate restrictions force a lot of units to be online to provide sufficient ramping capability. To minimize curtailment as much as possible, these units will frequently operate near their minimum stable operating point, thereby inducing a lot of part-load efficiency losses. For this reason, the impact of neglecting part-load efficiency losses is higher in scenario C and D and in the low flex case (see Fig. 5.5a). Additionally, the drop in efficiency when operating in part load is also higher in the low flex case than in the high flex case (see Tab. 5.4. By comparing the capacity mix in the reference case to the capacity mix in the case which does not incorporate part-load efficiency losses in Fig. 5.6, it can be observed that not considering part-load efficiency losses results in only a minor shift in investments (towards more IRES and towards thermal units with higher part-load efficiency losses). As a result, not incorporating part-load efficiency losses results in negligible suboptimalities (see Fig. 5.5b).

If storage technology-types can provide reserves, thermal power plants are operated less in part-load, and hence considering part-load efficiency losses becomes less important for the projection of the total system costs (see hollow circles and triangles versus full circles and triangles for the simulations without PLEL in Fig. 5.5a). In terms of investments, we can observe from Fig. 5.6c-5.6d that neglecting part-load efficiency losses again results in fewer investments in storage technology-types, since it becomes slightly less expensive to provide reserves using thermal generators, but the impact is rather small.

Start-up costs

Neglecting start-up costs (SC) leads to a small underestimation of total system costs in all scenarios. The relative underestimation of the total system costs is between 1.5% and 3.5% whenever less flexible power plants are considered and systematically below 2.5% whenever highly flexible power plants are considered. In general, the impact becomes higher as the share of IRES is increased. For all considered scenarios, incorporating SC leads to a very minor shift from mid and baseload technology-types and/or IRES towards more peak-load technology-types with lower SC. In addition, in the cases considering storage, more investments in storage technology-types and particularly PHS can be observed when SC are being considered, indicating that PHS technology-types get part of their value by avoiding SC from thermal generators. However, due to the fact that overall, start-up costs induce only minor differences in terms of investments, the suboptimality induced by neglecting start-up costs is shown to be negligible for all scenarios (see Fig. 5.5b).

Minimum up and down time constraints

The impact of neglecting minimum up and down time (MUDT) constraints appears to be negligible across all considered scenarios and cases. As shown in Fig. 5.5a, the relative underestimation of the total system cost when neglecting MUDT constraints is systematically below 0.4%. Also the suboptimalities induced by neglecting start-up costs are very low. It must be noted that this result can be dependent on the fact that SC are considered. For instance, plants might rarely violate MUDT constraints due to the fact that SC might not make it cost-effective to start up or shut down a unit for a brief period. Therefore, these constraints might have an impact when start-up costs would not be considered. In this regard, it is relevant to note that we have considered two sets of cycling characteristics, in which either stringent or optimistic assumptions are taken regarding both the minimum up and down times as well as the start-up costs. Therefore, it can be the case that MUDT constraints become binding whenever stringent assumptions for the minimum up and down times are taken, but start-costs are considered to be relatively low.

5.4.3 A closer look at reserve constraints

As shown in the previous section, incorporating reserve constraints in planning models can have a very high impact on the results, both in terms of projected system costs as in terms of the capacity mix. At the least, these constraints were shown to be essential for investments in storage technology-types. Given this potentially high impact of reserve constraints, this section aims to have a closer look at the modeling of reserve constraints in planning models.

Importance of considering multiple flexibility options for the provision of reserves

From Fig. 5.5a, we observe that if storage systems can contribute to the provision of reserves, the impact of reserve requirements on the projected total annual system costs drops to below 2% in all considered scenarios (see the hollow circles and triangles in the "no RES" simulations in Fig. 5.5a).

Even if storage systems would for some reason not be available or cannot contribute to the provision for reserves, the impact of the reserve requirements for high penetration levels of IRES can be strongly reduced if (i) the sizing of variable renewable forecast error reserves (VRFER) requirements is based directly on the exposure to forecast errors, and (ii) IRES are further allowed to provide upward reserves for the other reserve types (i.e., FRR and SCR).

Recall that we have adopted the reserve sizing assumptions from NREL's Resource Planning Model (RPM) [161]. As shown in Tab. 5.5, Eq. (5.14) and Eq. (5.15), the VRFER requirements are assumed to be linear with the instantaneous power generation by IRES. As such, whenever there is curtailment of IRES, the required VRFER decrease slightly. However, as shown in Fig. 5.8, the exposure to forecast errors is reduced one-on-one by the scheduled curtailment. For simplicity, let us assume that a constant fraction α of the forecasted wind generation $\overline{W}$ is uncertain regardless of the forecasted wind generation. As illustrated in Fig. 5.8, under this assumption, the exposure to forecast errors can be expressed as $max((\alpha\overline{W} - curt_w), 0)$, where $curt_w$ represents the scheduled curtailment. In contrast, in the assumptions taken in the RPM, the required VRFER equal αgen_w, which can be rewritten as $\alpha\overline{W} - \alpha_w curt_w$. By comparing this last expression to the result derived earlier, it can be seen that the reduction of VRFER with scheduled curtailment is not sufficiently considered in the RPM. For scenarios with a high penetration level of IRES in which curtailment occurs frequently, the strong reduction of exposure to forecast errors with scheduled curtailment becomes important to consider.

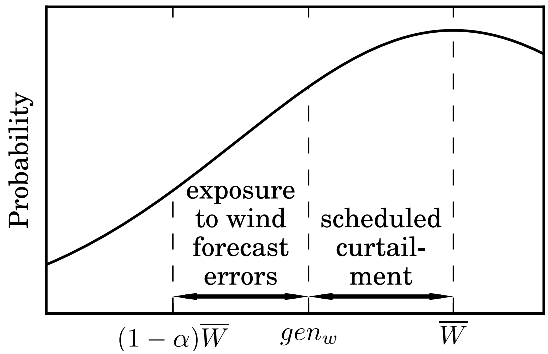


Figure 5.8: Illustration of the reduction of the need for VRFER by scheduled curtailment. A probability distribution of wind generation is presented. The forecasted wind generation when there would be no curtailment is indicated by $\overline{W}$. The wind generation that can be guaranteed with a reasonable certainty is indicated by $(1-\alpha)\overline{W}$, where α represents the uncertain fraction of the forecasted wind generation. The scheduled wind generation is indicated by gen_w.

Consider as an example a scenario with a high penetration of wind power where in a certain time step the forecasted wind power equals 60GW. Assume further that for some reason 20GW of curtailment is scheduled. Assuming that the uncertain fraction α equals 10% (of the forecasted 60GW), the VRFER sizing rules adopted in the RPM still result in a requirement of 10% of the remaining 40GW of wind power, implying a requirement for VRFER of 4GW. Given a forecast of 60GW, we would be maximally exposed to possible deviations of 6GW whenever there is no scheduled curtailment. However, since 20GW of curtailment was scheduled in this example, there is effectively no remaining exposure to forecast errors and hence there is no need to ensure VRFER in this example.

In addition, in such periods of massive curtailment (e.g., due to a strong oversupply of IRES), the scheduled wind generation might be below the level which can be guaranteed with reasonable certainty. In this case, there is no remaining exposure to IRES forecast errors. Additionally, the curtailment below the power level that can be guaranteed with a reasonable certainty can be used to provide upward reserves to cover other sources of uncertainty. This is illustrated in Fig. 5.9.

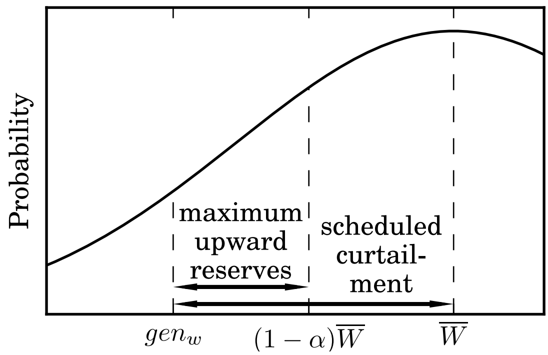


Figure 5.9: Illustration of the provision of upward reserves by IRES. A probability distribution of wind generation is presented. The forecasted wind generation when there would be no curtailment is indicated by $\overline{W}$. The wind generation that can be guaranteed with a reasonable certainty is indicated by $(1-\alpha)\overline{W}$, where α represents the uncertain fraction of the forecasted wind generation. The scheduled wind generation is indicated by gen_w.

Fig. 5.10 shows how the projected total system cost and the capacity mix in the low flex case changes when the sizing of VRFER requirements would be directly based on the exposure to VRFER and IRES are allowed to provide upward reserves. For the level of IRES generation that can be guaranteed with a reasonable certainty, we have taken the values corresponding to the original reserve sizing, i.e., 10% and 7.5% below the forecasted values for wind and solar respectively (see Tab. 5.5). The mathematical formulation for the sizing of VRFER and for the provision of upward reserves by IRES in the model is presented in Appendix C.

The results in Fig. 5.10 show that for high shares of IRES, even in the absence of storage technology-types, the impact of reserve constraints can be strongly

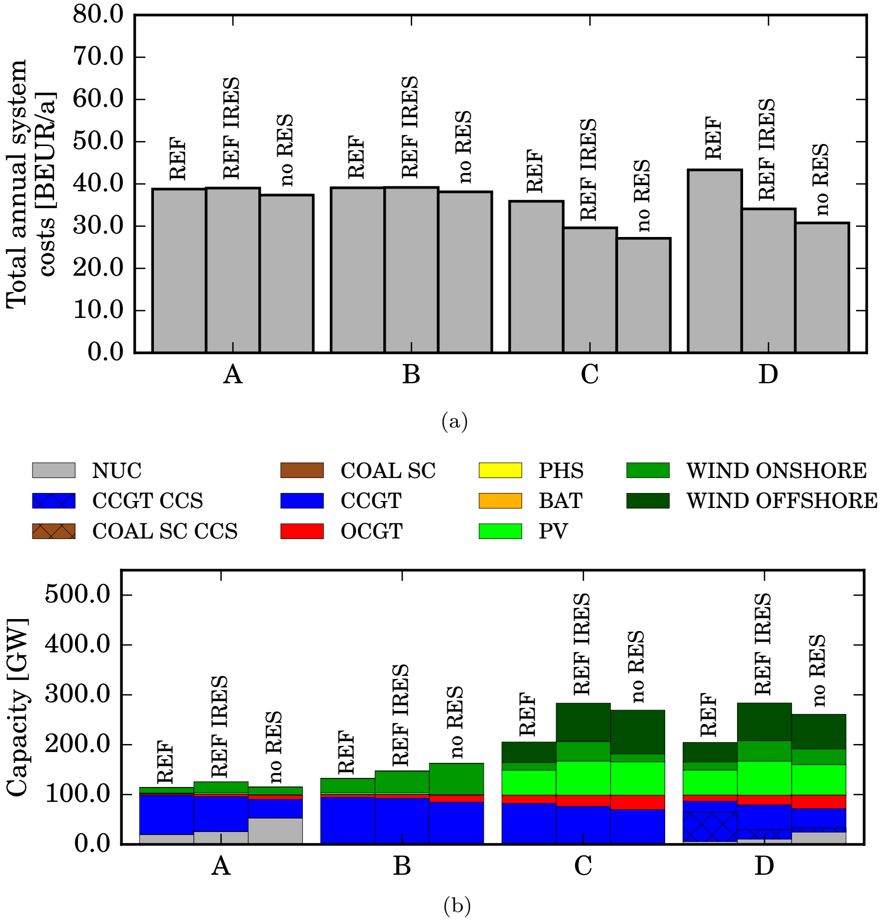


Figure 5.10: Projected total system costs (a) and capacity mix (b) in the low flex case for the simulations in which the sizing of the variable renewable forecast error reserves (VRFER) requirements correspond to the assumptions in NREL's Resource Planning Model and intermittent renewable energy sources (IRES) cannot provide upward reserves ("REF"), the simulations in which the sizing of VRFER requirements corresponds to the exposure to forecast errors and both thermal and IRES generators can provide upward reserves ("REF IRES ") and for the simulations which do not consider incorporating reserve requirements ("no RES").

mitigated by sizing the VRFER based on the exposure to forecast errors and by allowing IRES to provide upward reserves. In scenarios C and D, frequent periods of oversupply occur, during which IRES now provide all upward reserves[17]. Therefore, the need to curtail IRES and use more expensive thermal generators is strongly reduced. In scenarios with low penetration of IRES, there will be hardly be any curtailment, and hence almost no impact of adapting the reserve sizing rules or allowing IRES to contribute to the provision of reserves[18].

The implication of these findings is that when reserve constraints with simplistic reserve sizing rules are incorporated in planning models and storage technology-types or other flexibility options apart from thermal generators are not explicitly considered to contribute to the provision of reserves, the incorporation of reserve constraints can possibly lead to unrealistically high projections of total system costs and suboptimally low penetration levels of IRES. Even more so, the errors introduced by incorporating such reserve constraints but not explicitly considering other sources of flexibility for the provision of reserves can be higher than, or of the same order of magnitude as the errors introduced by not considering any technical constraint (see e.g., Fig. 5.4a). Therefore, we conclude that it is absolutely crucial to consider other sources of flexibility for the provision of reserves. Additionally, the sizing of VRFER requirements must be based on the exposure to forecast errors when simulating scenarios with a high penetration of IRES.

Additionally, we observed earlier that, although reserve requirements, ramping constraints and minimum operating point constraints have only a limited impact on the total system cost projections and investments in IRES as well as thermal generators when storage systems can contribute to reserves, these constraints remained key for investments in dedicated flexibility providers such as storage technology-types. As such, the incorporation of reserve constraints is mainly important to analyze the specific role of these flexibility providers. However, different flexibility providers are in direct competition with each other. Therefore, it is important to consider these different flexibility providers for making conclusions regarding the need for each of these [155]. Tab. 5.8 illustrates how sensitive the investments in storage in general, and BESS in particular, are to the cycling characteristics of thermal power plants and the ability of IRES to provide upward reserves. Other flexibility providers are not

[17]In periods of a strong oversupply, it is observed that IRES supply the entire demand and ensure sufficient upward reserves. Such situations do however raise questions regarding whether there is sufficient inertia in the system to ensure frequency stability. These issues deserve further attention but are not considered here.

[18]In Fig. 5.10a, in scenario A and B, the total system cost is shown to be slightly higher whenever the VRFER sizing rules are adopted and IRES are allowed to provide upward reserves. This is purely due to the fact that a higher optimality gap was required for solving these simulations within 16 hours.

considered here, but should be considered when analyzing the need/potential of storage technology-types.

Installed capacity [GW]	C				D			
	low flex		high flex		low flex		high flex	
	REF	IRES	REF	IRES	REF	IRES	REF	IRES
PHS	13.8	13.8	12.0	11.6	20.4	20.2	17.8	17.4
BESS	5.6	5.5	1.9	0.4	4.8	4.3	1.1	0.8

Table 5.8: Investments in storage technology-types for the different cases and scenarios considered. Additionally, the investments in storage technology-types whenever the sizing of variable renewable forecast error reserves (VRFER) is based on the exposure to forecast errors and intermittent renewable energy sources (IRES) are allowed to provide upward reserves are shown (indicated by IRES).

Uncertainties and simplifications in modeling reserve constraints in planning models

Characterization of reserve requirements Tab. 5.9 presents an overview of how reserve requirements are characterized in a number of state-of-the-art planning models. From this table, it can be observed that between different models, significant differences exist in terms of sizing of reserve requirements and the required activation times (and whether or not fast-starting units can provide reserves). The methodologies used to size reserves in planning models are typically highly simplified. As discussed before and shown in Tab. 5.9, in most state-of-the-art models, the sizing of reserves is not directly related to the exposure to IRES forecast errors whenever there is scheduled curtailment[19]. In addition, different sources of uncertainty (e.g., demand forecast errors, wind generation forecast errors and solar generation forecast errors) are often treated independently which can lead to an overestimation of the required reserves. Given that the impact of reserve constraints increases more than linear with the required volume, and that also the required activation times can play an important role, validation of these simplified reserve sizing approaches is required.

Provision of reserves Fig. 5.5a clearly illustrates how the impact of incorporating reserve constraints is dependent on the cycling characteristics

[19] As discussed earlier, this will only play a significant role for scenarios with a high penetration of IRES.

Model	Reserve type	Sizing	Activation time
RPM [161]	Frequency Regulation Reserves	1% of demand	Sub 5 minutes, 100% spin
	Spinning Contingency Reserves	Maximum of 6% of demand and the largest contingency	10 minutes, 50% spin
	Variable Renewable Forecast Error Reserves	10% of wind generation + 7.5% of solar generation	1 hour, 100% spin
ReEDS [84]	Frequency Regulation Reserves	1.5% of demand	Sub-minute, 100% spin
	Contingency Reserves	6% of demand	10 minutes, 50% spin
	Variable Renewable Forecast Error Reserves	Maximum difference in generation output between 2 consecutive hours in the last 15 days	roughly an hour, 17% spin
NETPLAN [149]	Regulation Reserves	To cover 99% of net load variations on 1-min time frame	1 minute
	Frequency Regulation Reserves	1% of demand	Sub 5 minutes, 100% spin
	Contingency Reserves	Largest contingency	10 minutes
	Spinning and load following reserves	Based on net load variability on 10-min time frame	10 minutes
	Replacement reserves		30 minutes

OSeMOSYS enhanced [127]	Primary Reserves	Largest contingency + 3 standard deviations of net load forecast error over half an hour	within seconds
	Secondary Reserves	3 standard deviations of net load forecast error over a 4 hour interval	15 minutes, 33% spin
Palmintier and Webster [154]	Regulating Reserves	1% of demand + 0.385% of installed wind capacity	5 minutes
	Load following and Spinning Contingency Reserves	Maximum of two largest generators and 3.3% of demand + 7.95% of installed wind capacity + 13.9% of instantaneous wind generation	10 minutes, 50% spin
De Jonghe et al. [114]	Reserves	6.5% of installed wind capacity + 12.5% of instantaneous wind generation	60 minutes

Table 5.9: Overview of the reserve requirements adopted in different planning models.

of thermal power plants (circles verus triangles in the "no RES" simulations). Aside from the ramping rate, minimum operating point and part-load efficiency losses, other assumptions regarding the provision of reserves can play a key role. For thermal generators, this is mainly the start-up time and whether or not fast-starting units can provide certain types of reserves. In addition, for storage technology-types, assumptions need to be made regarding the required energy content (related to the likelihood of reserves to be activated a number of consecutive time steps), whereas for IRES, one needs to determine the maximal generation level which can be guaranteed with reasonable certainty.

We conclude by stating that caution is needed when implementing reserve requirements in planning models. First, if different sources of flexibility are not considered for the provision of reserves, the impact of reserves can be severely overestimated. Second, planning models typically make assumptions regarding both the sizing of reserves, the required activation time of different types of reserves as well as the extent to which different technology-types can contribute to the provision of reserves.

5.4.4 Reduced formulations of the clustered UC problem for integration in planning models

This section aims to derive reduced formulations of the CUC constraints which are able to capture the most important technical aspects but reduce the computational cost of incorporating technical constraints in planning models. This is done by adapting and/or eliminating certain constraints and variables. The insights provided in Section 5.4.2 regarding which constraints have a significant impact on the results and the mechanism causing this impact will be leveraged here. Different model variants are considered in which the modeling detail will be gradually reduced.

Model variants with different levels of technical detail

The following model variants, each with a different level of technical detail, will be considered:

- REF: Reference model with all clustered unit commitment (CUC) constraints and integer commitment variables
- RELAXED: REF + continuous commitment variables
- STRIPPED: RELAXED + no minimum up and down time (MUDT) constraints + no ramping costs + no hourly ramp constraints + combined reserve types
- REDUCED: STRIPPED + no start-up or shut-down ranges and associated variables ($n^{su}_{gd,p,t}, n^{sd}_{gd,p,t}, n^{c,su}_{sm,p,t}, n^{c,sd}_{sm,p,t}, n^{d,su}_{sm,p,t}, n^{d,sd}_{sm,p,t}$)
- SIMPLE: REDUCED + no commitment constraints and associated variables ($n^{on}_{gd,p,t}, n^{c,on}_{sm,p,t}, n^{d,on}_{sm,p,t}$) + no start-up costs (SC)

- MO: no consideration of technical plant-level or system-level constraints

Below, the specific model adaptations of the RELAXED, STRIPPED, REDUCED and SIMPLE model variants are presented in more detail.

RELAXED model In the RELAXED model, all technical constraints are preserved. The only difference with the reference model is that the integer commitment variables as well as the variables for the number of units starting up and shutting down, i.e., $n^{on}_{gd,p,t}, n^{su}_{gd,p,t}, n^{sd}_{gd,p,t}$ and the similar variables for PHSs are replaced by continuous variables. The implication is that the model is allowed to have for instance 3.6 nuclear power plants online. As such, this model cannot account for the discrete nature of individual power plants.

It is sometimes argued that binary or integer variables are required to model operational limitations such as a minimum operating point and minimum up and down times as well as start-up costs (see e.g., [171]). However, it must be noted that these aspects are reflected in the RELAXED model. Whenever for instance 0.8 units of a certain technology-type with a nominal capacity of 1000MW and a minimum stable operating point of 500MW are started up, Eq. (5.21) will ensure that these 0.8 units will have to generate at least 400MW. Similarly, Eq. (5.27) will warrant that these 0.8 units will have to remain online for a number of hours, and Eq. (5.6) will allocate starting costs to bringing these 0.8 units online. Rather than binary or integer variables, it is thus the distinction between committed capacity and the instantaneous electricity generation which is required to account for these operational aspects.

STRIPPED model Next to relaxing the problem by using continuous rather than integer commitment variables, the STRIPPED model eliminates all constraints which were shown to have a negligible impact on the model results. These include minimum up and down time (MUDT) constraints, hourly ramp constraints as well as ramping costs.

Additionally, different types of reserves are combined. This is based on the fact that reserve constraints can force units online to provide sufficient head room and ramping capability. The required head room depends on the total requirement of spinning reserves and is independent of the time frame for activation (at least, assuming that fast-starting units cannot contribute to the provision of these reserves). In contrast, the number of units which need to be online to provide the required ramping capability for the provision of spinning reserves depends on both the required volume and the activation time of the different reserve types. Considering Eq. (5.30), it can be derived that the ramping constraint for the provision of spinning reserves is most binding for the reserve type for which the ratio between the required volume of reserves with activation times equal to or below that of the specific reserve type, and the activation time of this reserve type is the highest. In our case, this is the case for the SCR reserve type[20]. Based on these insights, one could reduce the number of reserve types, and hence the number of variables and equations one considers in a planning model. In the low flex case, both the ramping constraint and the head room constraint have an impact on the results. As such, one could combine the FRR and SCR reserves into one equivalent reserve type, where the demand for reserves of this type equals the sum of the demand for FRR and SCR reserves, and the activation time corresponds to the activation time for SCR reserves. Whenever the ramping constraints do not become binding (e.g., in the high flex cases), the head room constraint will be the only factor restricting the provision of spinning reserves, and hence, the required activation time is less relevant. As such, one could pool all reserve types into a single type, where the required volume equals the sum of the volumes of all reserve types and the activation time is equal to that of the slowest reserve type.

Fig. 5.11 shows the errors introduced by combining different reserve types. This shows that combining FRR and SCR reserves does not have an impact for any of the simulations. In contrast, combining all reserve types only provides accurate results whenever ramping constraints do not become binding (or whenever other sources of flexibility will provide these reserves at lower costs even when ramping constraints are relaxed). To ensure a model which remains accurate for a variety of assumptions regarding the flexibility of thermal power plants, we will only combine the FRR and SCR reserves in the STRIPPED model variant.

REDUCED model In this model variant, all adaptations of the STRIPPED variant are included. Additionally, the variables for the number of units starting up and shutting down in each period, i.e., $n^{su}_{gd,p,t}, n^{sd}_{gd,p,t}$ and the similar variables for PHSs, are eliminated. These variables were first of all used to model the minimum up and down time (MUDT) requirements (Eq. (5.27)-(5.28)). However, MUDT requirements were shown to have a negligible impact and are therefore not considered in this model variant. Second, the variable for the number of units starting up was used to define the start-up costs (SC) (Eq. (5.6)). However, the start-up costs can be determined based on the difference between committed units in adjacent time segments (i.e., $n^{on}_{gd,p,t+1} - n^{on}_{gd,p,t}$). Third, the variables for the number of units starting up and shutting down are used to restrict the generation level directly after a start-up and directly before a

[20] It might not be possible to unambiguously identify a single reserve type which will be most binding in terms of ramping requirements. This because it can be the case that a certain reserve type is most binding in some periods, while another reserve type is most binding in other periods.

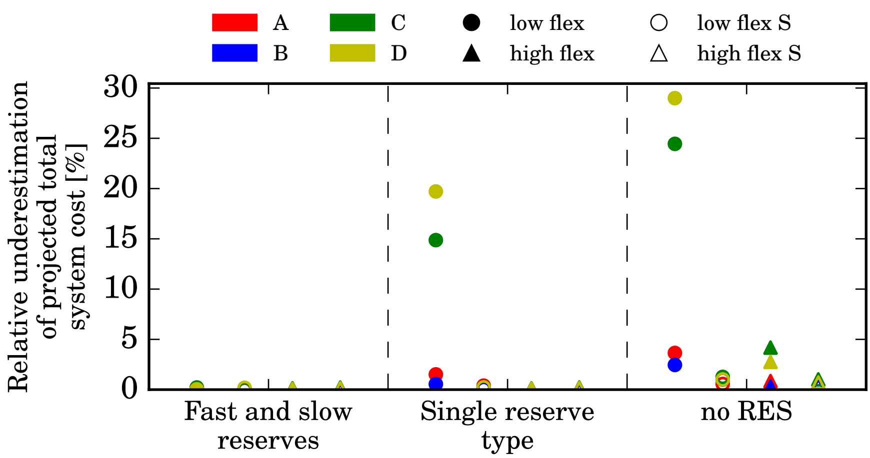


Figure 5.11: Relative underestimation of the projection of the total system costs for the different scenarios and cases when different reserve types are combined.

shutdown (Eq. (5.22)-(5.24)). However, the maximum power output directly after a start-up and directly before a shut-down are assumed to be close to the rated capacity in the low flex case and equal to the rated capacity in the high flex case[21]. Therefore, assuming that plants are able to operate at the maximum operating point directly after a start-up or directly before a shut-down is expected to have a minimal to no impact. Finally, the variable for the number of units shutting down is used to restrict units which will shutdown from providing upward spinning reserves (Eq. (5.30)).

The REDUCED model presented here resembles the advanced enhanced OSeMOSYS model described in [128, 127]. The main difference is that the enhanced OSeMOSYS model does not consider SC (due to the very low level of temporal detail used in this model).

SIMPLE model In this model variant, the commitment variables, i.e., $n^{on}_{gd,p,t}$ and the similar variables for PHSs, are eliminated. The commitment variables are essential for modeling nearly every detailed technical constraint, including the minimum stable operating point (MSOP), ramping and head-room restrictions as well as start-up costs. Therefore, alternative ways of approximating these constraints need to be considered.

[21]The values for SU_{gd} and SD_{gd} assumed here correspond to the minimum operating point plus the ability to ramp within one hour

Particularly, the head room and ramping constraints for the provision of reserves together with the MSOP can have a significant impact on the dispatch. More specifically, in order to provide a certain amount of spinning reserves, sufficient head room and ramping capabilities must be ensured which, due to the MSOP constraints, require a certain amount of power generation. It can be noted that more head room and ramping capabilities can be realized by committing more units (which however comes at the cost of higher levels of curtailment, part-load efficiency losses and start-up costs). Considering this, we relax the constraints which ensure that there is sufficient head room and ramping capability by assuming that the maximal possible number of units are online for a given power output level (corresponding to the situation in which all units are operating at the minimum operating point). This means that for a certain power output level $gen_{g,p,t}$, the number of online units is assumed to be $gen_{g,p,t}/\underline{P}_{gd}$ (or vice versa, when this number of units needs to be online in order to provide reserves, they are generating at least $gen_{g,p,t}$). As such, Eq. (5.22) and Eq. (5.30) can be replaced by the following constraints; respectively:

$$gen_{gd,p,t} + \sum_{r \in \mathcal{R}} r^{+,spin}_{r,gd,p,t} \leq \frac{gen_{gd,p,t}}{\underline{P}_{gd}} \overline{P}_{gd} \quad \forall gd \in \mathcal{GD}, p \in \mathcal{P}, t \in \mathcal{T}. \tag{5.69}$$

$$\sum_{r \in \mathcal{R}: T^{ACT}_{r} \leq T^{ACT}_{r'}} r^{+,spin}_{r,gd,p,t} \leq \frac{gen_{gd,p,t}}{\underline{P}_{gd}} \overline{P}_{gd} \frac{R_{gd}}{100} T^{ACT}_{r'}$$

$$\forall r' \in \mathcal{R}, gd \in \mathcal{GD}, p \in \mathcal{P}, t \in \mathcal{T}. \tag{5.70}$$

Start-up costs are not considered within the SIMPLE model. In principle, it is possible to attach costs to the change in generation output. However, given that the number of units online is not tracked, one cannot distinguish between changes in generation output of a technology cluster which are the result of start-ups and changes in generation output of a technology cluster due to ramping units up and down.

The SIMPLE model presented here has some resemblance with the model developed by De Jonghe et al. [114]. In their model however, the instantaneous generation level is used as an approximation for the committed capacity in the ramping constraint, which is too stringent. In addition, their model does not consider head room constraints for the provision of spinning reserves.

Accuracy of model variants with different levels of technical detail

To evaluate the accuracy of the presented reduced formulations of the clustered unit commitment (CUC) model, the same scenarios and cases as in the previous sections will be used. In the previous sections, we have indicated that in some of these cases (notably the low flex S case), stringent assumptions regarding the availability of flexibility were taken which could lead to strong overestimations of the total system costs and the difficulty of integrating IRES. In addition, we have suggested that by adapting the methods used for the sizing of reserves and by allowing IRES to provide reserves, the model results could be improved. Nevertheless, the same cases and the original assumptions regarding the sizing of IRES and the participation of IRES to the provision of reserves (i.e., the lack thereof) are adopted here. The model with all technical constraints will serve as a reference despite the fact that, due to certain assumptions made in some of the cases, the reference model might give unrealistic results. In this regard, it must be noted that in this section the focus is purely on approximating the technical constraints of thermal power plants and storage technology-types (given certain assumptions regarding the sizing of reserve requirements and the available flexibility).

Fig. 5.12 presents the accuracy in terms of projecting the total system cost for the different levels of technical detail considered. In addition, Fig. 5.13 presents the impact of the level of technical detail on the capacity mix for all considered scenarios and cases. From these figures, we can observe that relaxing the problem by replacing the integer commitment variables by continuous variables has a negligible impact on the obtained results (RELAXED model variant). In terms of projecting the total system cost, the underestimation of costs is systematically below 0.6%[22]. In addition to relaxing the integrality constraits of the commitment variables, neglecting the minimum up and down time constraints, hourly ramping constraints, ramping costs and combining reserves (STRIPPED model variant) also does not significantly impact the results. Finally, also omitting the start-up and shut-down variables does not introduce significant errors (REDUCED model variant).

The assumptions that needed to be made in the SIMPLE model variant do turn out to have a significant impact on both the cost and the capacity mix. Nevertheless, particularly in the low flex case, these remaining constraints still make a notable improvement with respect to not including any technical constraints (MO). In this regard, it must be noted that the SIMPLE model variant mainly aims to capture the implications of providing spinning reserves

[22]In small power systems such as island systems, the discrete nature of individual units can possibly have a significant impact on the results. However, the focus here is on large, interconnected power systems.

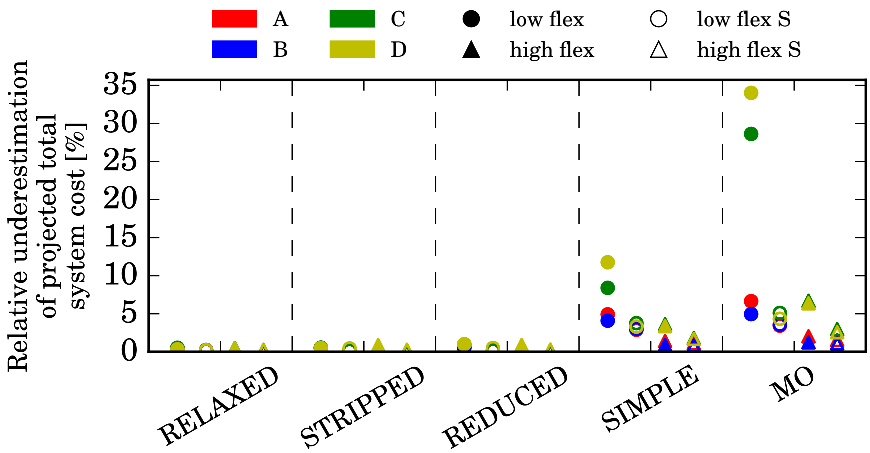


Figure 5.12: Relative underestimation of the projection of the total system costs for the model variants with different levels of technical detail. A description of these reduced model formulations are presented at the onset of Section 5.4.4.

using thermal generators. In the cases with more flexibility (high flex case, or the cases with storage), the provision of reserves is less costly, and the SIMPLE model variant offers only a limited improvement over models which do not consider technical constraints. This is due to the fact that other technical aspects, such as start-up costs and part-load efficiency losses are not considered in this model variant. In addition, due to the relaxation of the head room and ramping constraint, the SIMPLE model does not fully capture the cost related to the provision of reserves. As a result, the SIMPLE model has a slight bias towards more baseload technology-types and IRES, at the expense of flexible technology-types. This last observation can be clearly noticed by looking at the level of investments in storage technology-types in the SIMPLE models which are somewhere in between the level of investments in storage technology-types in the reference model and the MO model (see Fig. 5.13c- 5.13d).

To put the accuracy of the reduced formulations in perspective, the magnitude of the differences in results introduced by reducing the level of technical detail can be put alongside the magnitude of the differences in results following from the choice of cycling characteristics of thermal power plants[23]. This is visualized

[23] Aside from the uncertainty regarding the flexibility of thermal power plants, there might be other uncertainties which can have a significant impact on the results, such as e.g., the degree of forecast errors in the future and the opportunities for utilizing other sources of flexibility.

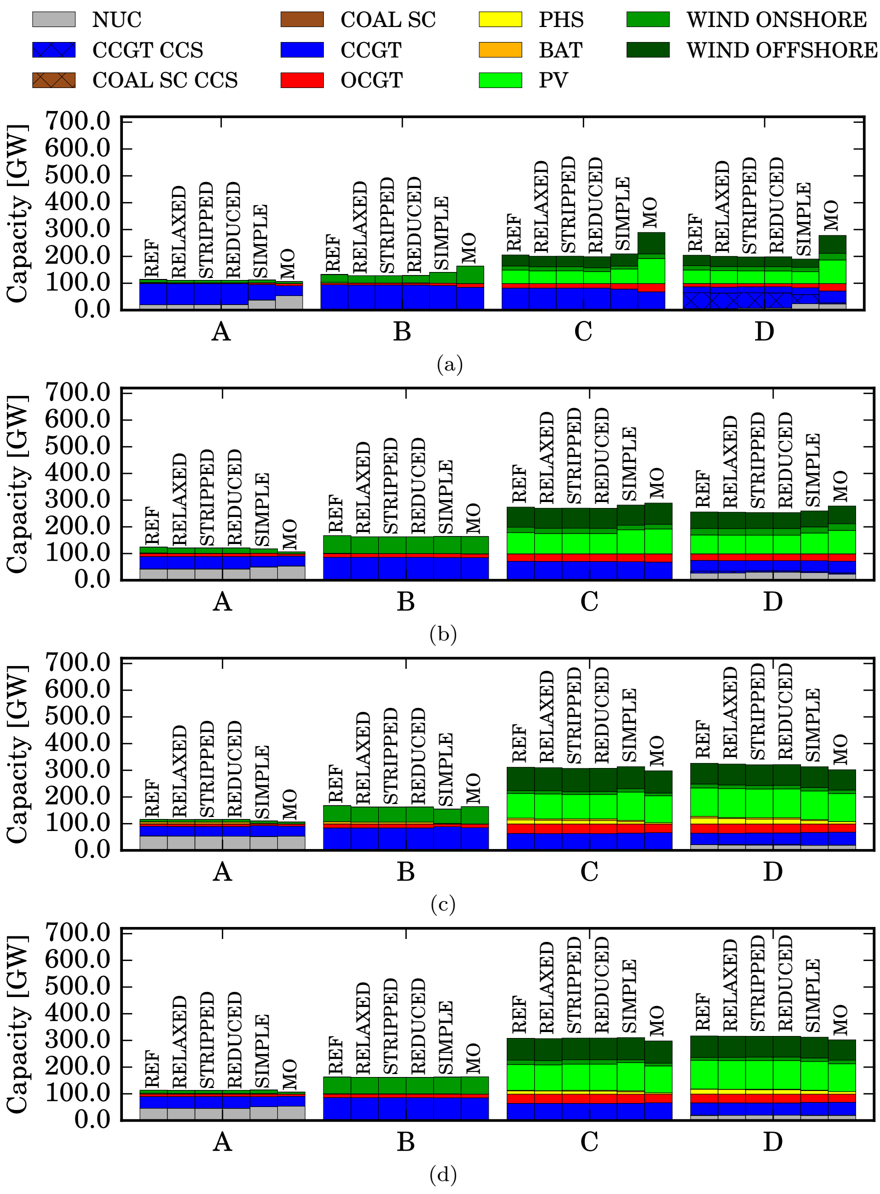


Figure 5.13: Capacity mix for the model variants with different levels of technical detail for the different scenarios in the low flex case (a), the high flex case (b), the low flex S case (c) and the high flex S case (d).

in Fig. 5.14-5.15 for the cases without and with the possibility to invest in storage respectively. Since the accuracy of the RELAXED, STRIPPED and REDUCED model variants are very similar, only the REDUCED model variant is depicted.

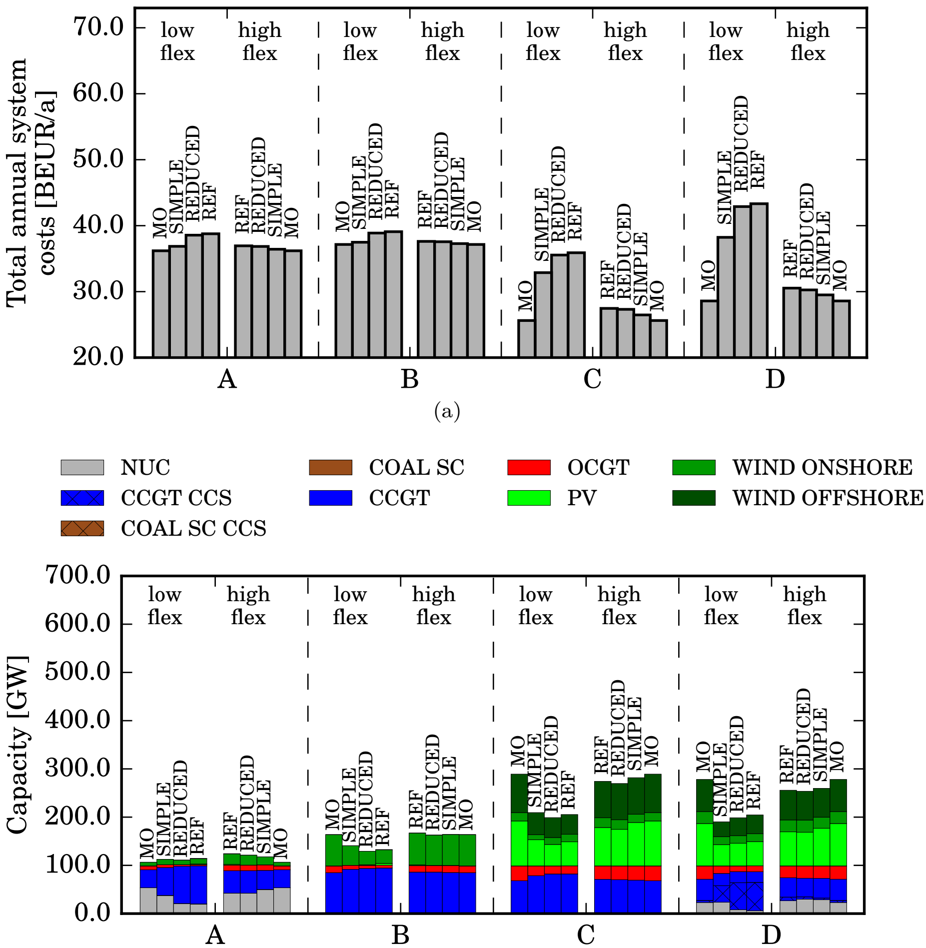
From these figures, it can be observed that for all considered cases, the errors introduced by reducing the technical detail in the REDUCED model variant are significantly smaller than the assumptions taken regarding the flexibility of thermal power plants. **We can therefore conclude that the RELAXED, STRIPPED and REDUCED models are currently more than accurate enough**, i.e., given the large range of cycling parameters being reported in the literature, more detailed modeling of the technical constraints than is done in the RELAXED, STRIPPED and REDUCED brings very little added value.

Even for the SIMPLE model variant, the errors introduced by using such a simplified technical representation are maximally of about the same order of magnitude as the differences in results when different assumptions are taken regarding the flexibility of thermal power plants. However, as mentioned above, the SIMPLE model variant does introduce a clear bias. Therefore, if one would actively explore the impact of the choice of cycling characteristics using the SIMPLE model variant, the results will not accurately reflect the range of outcomes.

Computational performance of model variants with different levels of technical detail

The calculation times of the different model variants for all considered cases and scenarios are presented in Fig. 5.16. This figure shows that considerable reductions in computation time can be achieved by relaxing the commitment variables and eliminating certain constraints. The REDUCED model variant is shown to be a factor 5-600 faster than incorporating the CUC constraints while introduced errors were shown to be negligible[24]. Even with respect to the RELAXED model, the REDUCED model is a factor 2-10 faster. Nevertheless, it can be observed that not including any technical constraints remains about

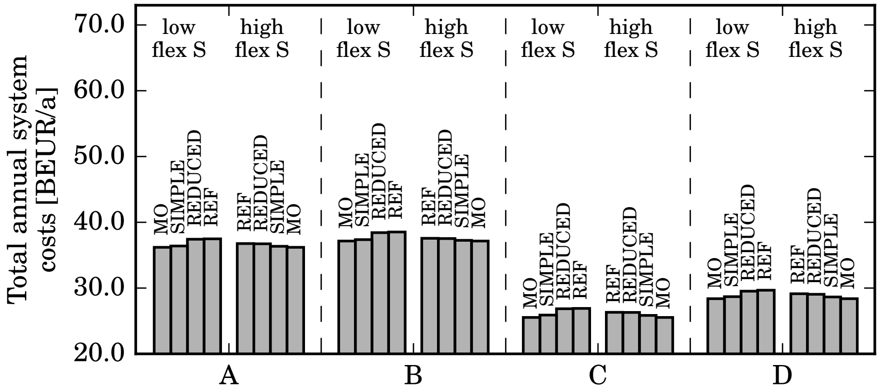
[24]It must be noted that the computation time of the planning model with integrated clustered unit commitment constraints (REF) is strongly dependent on the optimality gap used. As stated earlier, we have used a relative gap of 0.5%. Whenever a higher gap would be used (e.g., 2%), the computation time of the reference simulations would likely be significantly lower. Increasing the optimality gap therefore also forms an interesting option to decrease the computation time, but this option is not explored in this work.



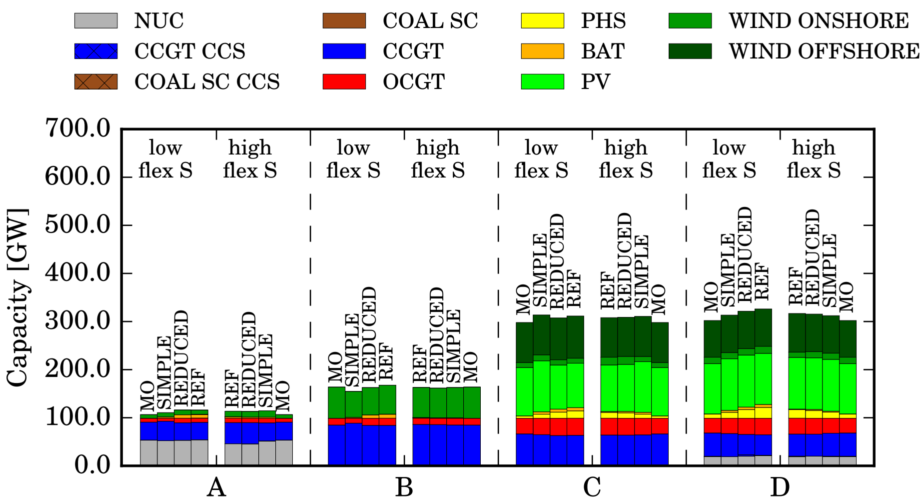
(a)

(b)

Figure 5.14: Accuracy of the reduced model formulations relative to the impact of the choice of cycling characteristics for the cases without storage. The reference simulations with the different assumptions regarding the cycling characteristics of thermal power plants are put side by side to visualize the impact of the choice of cycling characteristics. The results are shown for the projected total annual system cost (a), and the optimal capacity mix (b).



(a)



(b)

Figure 5.15: Accuracy of the reduced model formulations relative to the impact of the choice of cycling characteristics for the cases with storage. The reference simulations with the different assumptions regarding the cycling characteristics of thermal power plants are put side by side to visualize the impact of the choice of cycling characteristics. The results are shown for the projected total annual system cost (a), and the optimal capacity mix (b).

an order of magnitude faster than the REDUCED model[25]. With respect to the REDUCED model, the SIMPLE model further reduces the computation time by a factor of 1.5-3. More detailed information regarding how the different model variants reduce the number of equations, variables and computation time are presented in Appendix D.

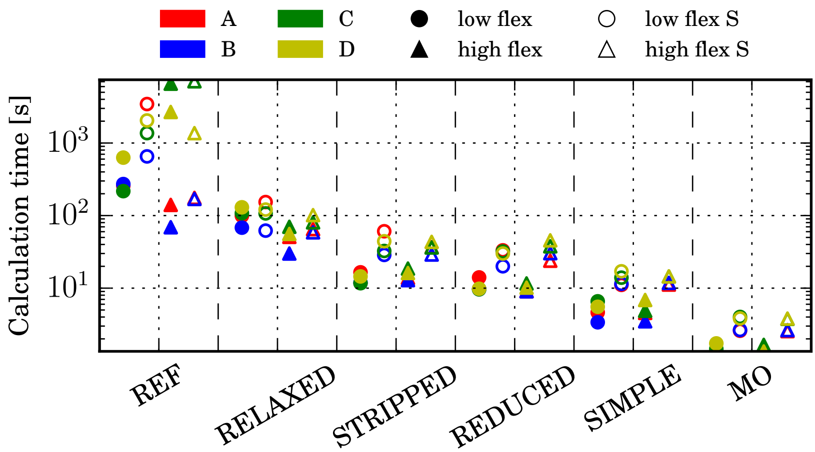


Figure 5.16: Calculation time for the model variants with different levels of technical detail for all considered scenarios and cases.

Depending on the computational resources available, the RELAXED and REDUCED models are shown to provide a good trade-off between accuracy and computational complexity. The REDUCED model has the advantage that it is faster. In contrast, the RELAXED model has the advantage of being more robust in terms of accuracy. Although in all our simulations, the accuracy of the RELAXED model did not significantly deviate from that of the REDUCED model, it could be possible that the accuracy of the REDUCED model is lower whenever e.g., larger minimum up and down times or lower start-up and shut-down ranges are assumed.

[25] It is important to note that in energy-system optimization models where the power sector is merely one part of the entire optimization problem, it can be expected that the relative difference in computation time becomes lower.

Reflections on common methods used for accounting for flexibility in the literature

As discussed in Section 5.1, different state-of-the-art planning models have different ways of accounting for technical constraints. Here, some reflections are made on some of the more common approaches.

First, certain state-of-the-art power system optimization models such as NREL's Resource Planning Model (RPM) [87, 130], MIT's Investment Model for Renewable Electricity Systems (IMRES) [73] and the models developed by Jin et al. [131] and Kirschen et al. [48] use binary commitment variables for individual plants. Moreover, the investment planning model with CUC constraints developed by Palmintier and Webster [88, 8, 156] uses integer variables to describe the number of units which are online within each technology cluster. However, as Fig. 5.16 shows, using binary or integer commitment variables strongly increases the computational cost, which might come at the expense of limitations in the scope of the model or the level of temporal, spatial and technological detail that can be included. Moreover, the results presented above show that this level of detail is needlessly high given the small deviations resulting from relaxing the integrality conditions of the commitment variables in comparison to the significant deviations which result from the assumptions taken regarding the cycling characteristics of thermal power plants[26].

Second, a number of models do not use separate variables for power generation and committed/online capacity. In these models, the maximum ramp that can be delivered by a certain technology-type is frequently based on the installed rather than the committed capacity (since the latter is not tracked). For example, the ramping constraint for the provision of spinning reserves (Eq. (5.30) in the CUC model) in these models become:

$$\sum_{r \in \mathcal{R}: T_r^{ACT} \leq T_{r'}^{ACT}} r_{r,gd,p,t}^{+,spin} \leq cap_{gd}^{av} \frac{R_{gd}}{100} T_{r'}^{ACT}$$

$$\forall r' \in \mathcal{R}, gd \in \mathcal{GD}, p \in \mathcal{P}, t \in \mathcal{T}. \tag{5.71}$$

Such constraints can for instance be found in the NETPLAN model [149] and the PERSEUS-RES-E model [45]. In addition, a similar constraint but now for ramping between consecutive time steps is found in the model developed by Aboumahboub et al [151]. Moreover, in both NETPLAN and PERSEUS-RES-E as well as in the ReEDS model [84], the provision of reserves is restricted by a head room constraint in which the maximum head room is defined as the

[26] Small power systems, such as island systems, possibly form an exception, since the discrete nature of individual power plants becomes more important for smaller systems.

difference between the instantaneous power generation and the installed capacity [149, 45, 84], i.e., Eq. (5.22) in the CUC model would now look as follows:

$$gen_{gd,p,t} + \sum_{r \in \mathcal{R}} r^{+,spin}_{r,gd,p,t} \leq cap^{av}_{gd} \quad \forall gd \in \mathcal{GD}, p \in \mathcal{P}, t \in \mathcal{T}. \tag{5.72}$$

These constraints effectively imply that no distinction is made between online and offline capacity, i.e., both the ramping capability and the head room available are dependent on the installed capacity rather than the committed capacity as would be the case for the provision of spinning reserves. The result is that the ability to provide upward reserves is restricted purely by the installed capacity and that reserve requirements will not significantly affect the dispatch. However, as our results have shown, the impact of including reserve constraints is due to the necessity to have sufficient flexible units online (which therefore might displace less expensive generators and lead to curtailment of IRES) rather than simply available.

Finally, in more stylized models, must-run requirements are frequently used for baseload technology-types such as nuclear and coal-fired power plants. In our detailed simulations, the results of the scenario with high shares of IRES in combination with nuclear as the baseload technology (scenario D) clearly show the cycling behavior of nuclear power plants, with power output varying between 0 and rated capacity in all cases. Must-run requirements on an annual or seasonal time frame are thus likely to be overly stringent, especially for scenarios with high shares of IRES.

5.5 Summary and conclusions

To limit the computational complexity of long-term planning models such as energy-system optimization models (ESOMs) and power-system optimization models (PSOMs), technical constraints on both the system level (e.g., the need for operating reserves) and the plant level (e.g., limited ramping rates) are typically not incorporated or represented in a highly stylized manner. As shown in Chapter 3, not incorporating technical constraints can introduce a technology bias towards less flexible baseload technology-types and intermittent renewable energy sources (IRES). Nevertheless, currently only a limited number of state-of-the-art PSOMs do integrate detailed technical constraints.

This chapter has focused on incorporating detailed technical constraints in long-term planning models. The first main objective of this chapter was to determine how important/relevant it is to consider these technical constraints in long-term planning models. To this end, a planning model with integrated clustered unit commitment (CUC) constraints has been developed and the results of this model were compared to the results provided by a model which does not incorporate technical constraints (referred to as the merit order (MO) model). Four scenarios (with a high and low penetration of IRES and with or without nuclear plants as baseload technology-types) have been considered to analyze the dependency of the results on the capacity mix. In addition, four cases have been set-up to analyze the importance of the assumptions regarding the flexibility of thermal power plants and the availability of other sources of flexibility (represented by the ability to invest in storage technology-types here).

The results have shown that for the majority of the considered scenarios and cases the impact of neglecting technical constraints in planning models is rather limited, both in terms of the impact on projections of the total system costs and in terms of the impact on the capacity mix. The main exception here relates to the impact on investments in storage technology-types, for which incorporating technical constraints was shown to be key. For this reason, we conclude that whenever one is not specifically interested in the role of storage technology-types, and by extension, all dedicated flexibility providers, incorporating technical constraints is not essential. It must be noted that the presented analysis did not consider the flexibility that can be provided by increased interconnections and by a flexible demand side. Whenever these elements would be included, the impact of considering technical constraints will likely be even smaller.

The second main objective of this chapter was to derive reduced formulations of the CUC constraints which can be tractably integrated in large-scale planning models. To this end, we first analyzed which specific constraints have the highest impact on the results and which constraints have a negligible impact on the results and can hence be omitted. Additionally, we have analyzed how the specific constraints which can have a significant impact on the results exactly influence the results.

The results have shown that minimum up and down time (MUDT) constraints as well as hourly ramping constraints have a negligible impact on the results for all considered scenarios and cases. Start-up costs (SC) on the other hand were shown to have a significant but limited impact on the results across all considered scenarios and cases, both in terms of the projected costs and the capacity mix. However, not incorporating start-up costs has a negative impact on investments in pumped hydro storages (PHSs) as these technology-types get part of their value from avoiding the start-up costs of thermal generators. In contrast, the impact of considering operating reserve requirements was shown to strongly depend on the share of IRES, the flexibility of thermal power plants and the availability of other sources of flexibility. Whenever thermal power plants are rather flexible or particularly whenever storage technology-types are available at a reasonable cost, the impact of reserve requirements on the projected total system cost and investments in IRES and thermal generators is rather low. Nevertheless, these reserve requirements were shown to be key for investments in storage technology-types.

Ramping constraints, minimum stable operating point (MSOP) constraints and part-load efficiency losses (PLEL) either limit the ability of thermal generators to provide spinning reserves or increase the cost at which these spinning reserves can be provided. These constraints hence help to correctly consider the competition between thermal generators and storage technology-types for the provision of operating reserves. Ramping rates restrict the amount with which the power output can be increased within the timeframe required for activation of the reserves. The impact of incorporating ramping rate restrictions for the provision of reserves was shown to be strongly dependent on the assumed flexibility of thermal power plants. Only when stringent assumptions were taken regarding the capability of thermal power plants to ramp, these constraints became binding. Aside from ramping rate restrictions, sufficient head room (i.e., the difference between the online capacity and the current power output) must be available in order to provide spinning reserves. As more (flexible) units are brought online, the ramping capability and head room provided by all units together is increased. Reserve requirements thus make sure that sufficient (flexible) units are online to ensure that the reserves can be provided when required. On the other hand, MSOP constraints impose that whenever a number of (flexible) units need to be online for the provision of reserves, these units must also generate a minimum amount of electricity and therefore possibly displace less expensive generators potentially leading to curtailment of IRES. MSOP restrictions are hence essential for capturing the costs related to the provision of spinning reserves by thermal generators and therefore have a strong impact on investments in storage technology-types (particularly in scenarios with a high penetration of IRES). Finally, reserve requirements force units to operate in part-load and therefore induce part-load efficiency losses.

The information regarding to what extent and how specific constraints impact the results was leveraged to derive reduced formulations of the CUC problem. A number of these reduced formulations, with a decreasing level of detail have been implemented and the results of these models have been compared to a reference investment planning model which incorporated the full CUC constraints. A first necessary step to reduce the computational cost was to use continuous instead of integer commitment variables (RELAXED model). Relaxing these variables was shown to have a minor impact on the results. Additionally neglecting hourly ramping constraints, MUDT constraints and restricted operating points directly after a start-up or directly before a shut-down (REDUCED model) also did not have a significant impact on the results. Even more so, the impact of the model simplifications in the REDUCED model was shown to be significantly smaller than the impact of the choice of cycling characteristics of thermal power plants. We therefore conclude that, given the large range of cycling characteristics of thermal power plants reported in the literature, the developed REDUCED model is more than accurate enough for long-term planning purposes. With respect to the reference planning model with integrated CUC constraints, this REDUCED model was shown to reduce the computation time by a factor of 5-600 for the different simulations. Nevertheless, the REDUCED model still required about 10 times as much computation time as the investment planning model which did not incorporate technical constraints.

Based on the presented results, some reflections were made on common methods for accounting for flexibility in planning models. A first reflection relates to the use of binary or integer commitment variables in certain state-of-the-art planning models. Our results indicate that this unnecessarily increases the computational cost. A second reflection relates to the use of must-run requirements for baseload technology-types. Based on our detailed simulations, these must-run requirements are likely to be overly stringent.

The presented analysis has also highlighted a possible pitfall whenever incorporating detailed technical constraints in planning models. First and foremost, there exists a risk that the incorporated technical constraints are overly and unrealistically restrictive. As our results have shown, whenever stringent assumptions are taken regarding the flexibility of thermal power plants and no other sources of flexibility are explicitly modeled, incorporating technical constraints can possibly lead to unrealistically high projections of total system costs and suboptimally low penetration levels of IRES. Reserve constraints were shown to be particularly important in this regard. We therefore conclude that it is essential to consider different sources of flexibility and how these different sources of flexibility can contribute to the provision of reserves when incorporating detailed technical constraints in planning models.

We have furthermore highlighted that, while reserve constraints are key for analyzing the role of storage technology-types, a number of strong assumptions regarding these reserve constraints are typically made. These include assumptions regarding the sizing and activation time of reserve requirements as well as assumptions regarding to what extent different technology-types can contribute to the provision of reserves. Given that these assumptions can have a significant impact on results, further research is required to validate these assumptions or to propose alternatives. Our findings thus suggest that one must be highly cautious when incorporating reserve requirements in planning models. If the focus of the developed scenarios is not on storage technology-types or other dedicated flexibility providers, we therefore suggest to not incorporate reserve requirements. In contrast, whenever the focus is on the role of dedicated flexibility providers, reserve requirements are important to consider but further research is required to challenge some of the assumptions made when modeling reserve requirements in planning models.

The work presented in this chapter also has a number of limitations which motivate further research. First, we have focused on large power systems. The presented conclusions might therefore not hold for small, isolated power systems. Second, we did not consider spatial aspects and related network constraints. In larger and highly interconnected power systems, the impact of not considering technical constraints will likely be lower. Similarly, the flexibility that can be provided by the demand side has not been considered. Finally, in all presented simulations, a planning reserve margin was introduced to which only thermal generators could contribute. As such, storage technology-types or IRES did not have the ability to reduce the total required capacity of thermal generators. If storage technology-types or IRES could contribute to the planning margin (or no planning margin would be incorporated), incorporating technical constraints might have a higher impact on the capacity mix and the projected system cost. Additionally, the endogneous determination of the capacity credit of storage technology-types and IRES in itself deserves further research.

Other aspects requiring further research include the endogenous sizing of operating reserves in planning models, and the investigation of other technical system-level constraints which can have an impact for scenarios with a high penetration of IRES (e.g., related to providing sufficient inertia to maintain a stable system). From the supply side of flexibility, also the development and validation of models for other sources of flexibility (e.g., demand response) and how these can contribute to the provision of operating reserves, as well as gaining more insight into the actual flexibility of thermal power plants deserves further attention.

Chapter 6

Limitations of optimization models for representing markets, policies and agent behavior

This chapter focuses on the limitations of using optimization models for creating descriptive scenarios. In such scenarios, the objective is to determine the likely evolution of the energy/electricity system when certain policies are implemented and assumptions are made regarding the evolution of fuel prices, technological progress, etc. To determine this likely evolution, the long-run or intertemporal market equilibrium is determined. As discussed in the introduction of this dissertation, in a deregulated market, investment decisions can be strongly influenced by the market design, policy interventions and the uncertainty faced by the agents. Therefore, the models used for developing these descriptive scenarios should be able to represent the impact of specific market designs, policy interventions and behavioral characteristics of the agents involved on the market equilibrium. In this regard, optimization models have certain limitations, i.e., if certain market designs or policy interventions are in place or certain assumptions are made regarding the behavioral characteristics of agents, optimization models cannot be used to determine the equilibrium. However, to the best of our knowledge, the literature contains no general overview regarding the limitations of optimization models in this regard.

The goal of this chapter is therefore to generate a general overview of the limitations of optimization models for computing the equilibrium (i.e., when optimization models are used from a descriptive perspective). We restrict ourselves to imperfect energy markets in which none of the agents behaves strategically, i.e., all agents are assumed to be price takers. For studies focusing on the impact of strategic behavior on investment decisions, we refer to [96, 109, 172, 173]. An overview of the limitations of optimization models helps to increase the awareness of the opportunities and limitations of optimization models which, given the amount of resources and the specific expertise required for developing large-scale planning models, is essential for deciding on a long-term strategy for the type of model to develop.

The outline of the remainder of this chapter is as follows. First, Section 6.1 sketches in more detail the context and motivation for the research within this chapter and presents an overview of the literature on this topic. Next, Section 6.2 provides the economic background on the use of optimization models to compute the market equilibrium. Section 6.3 analyzes the relation between optimization problems and equilibrium problems and derives the limitations of optimization models. These limitations are subsequently illustrated in Section 6.4 by presenting topical examples of equilibrium problems containing policies, market designs and behavioral characteristics which are relevant in the context of planning in deregulated electricity markets but cannot be solved directly using optimization models. Finally, Section 6.5 summarizes and presents the main conclusions.

6.1 Introduction

6.1.1 Use of optimization models in deregulated markets

The first applications of mathematical long-term power-system and energy-system planning models have taken place before the liberalization of the energy/electricity markets. In this context, a central planner (e.g., a government or a state-owned or regulated utility) faced the problem of determining a long-term investment plan which minimized the total cost of the energy provision. As such, long-term planning models were developed which were formulated as optimization problems.

However, since the liberalization and deregulation of electricity markets, investments in generating capacity and operational decisions are made by private generation companies (GenCos) aiming to maximize their profits. Hence, there is no longer a central authority which can plan investments in order to maximize welfare. Consequently, the role of power-system planning has changed from determining the optimal investment planning for direct execution, to steering the market outcome in the desired direction [174]. Despite this changing context, optimization models have remained to be the most popular tools for long-term energy-system and power-system planning [175].

As discussed in the introduction of this dissertation, optimization models serve two distinct purposes in a deregulated context. First, optimization models can be used to determine the cost-effective transition pathway from a societal perspective by maximizing welfare (i.e., a normative/prescriptive perspective is taken). Second, optimization models can be used to analyze the long-run or intertemporal market equilibrium (i.e., a descriptive perspective is taken). For the latter, optimization models rely on the fact that the total surplus (TS)[1] is maximized in the equilibrium found in competitive markets where different economic agents aim to maximize their own profit (relating to the famous invisible hand of Adam Smith) [25, 50, 51]. Thus, by maximizing the TS, the competitive equilibrium can be computed. As stated by Loulou et al. [25], this allows to "shift the model's rationale from a global, societal one (social welfare maximization) to a decentralized one (individual utility maximization)". The focus in this chapter is on the use of optimization models for developing scenarios which take a descriptive perspective.

A closer look at the modeling choices in some of the well-known power-system optimization models (PSOMs) and energy-system optimization models (ESOMs) reveals that most optimization models effectively take a descriptive, decentralized perspective to simulate the outcome of the energy markets. This is among others reflected in the choice of discount rates. Whereas optimization models aiming to find the socially optimal solution use a social discount rate, optimization models aiming to simulate the behavior of private agents in competitive energy markets typically use finance-equivalent discount rates[2] or implicit discount rates to reflect the opportunity cost of capital, the risk involved and other barriers [50, 176, 177]. These discount rates are frequently referred to as hurdle rates. For example, in the JRC-EU-TIMES model [111], a hurdle rate of 7% is applied for investments in centralized electricity generation, whereas for residential investments a hurdle rate of 17% is applied. Again different hurdle rates are used for investments in grid infrastructure, other industry and

[1] In this dissertation, we frequently refer to the objective function of optimization models as maximizing the total surplus, being the sum of the producer and the consumer surplus. It should be noted that it would be more general and correct to refer to the objective function of optimization models as maximizing the difference between the utility (i.e., the value related to consumption) and the production costs.

[2] As discussed in [51], optimization models cannot directly reflect heterogeneous discount rates (something which we discuss further in Section 6.4). Nevertheless, most optimization models make certain approximations to account for different discount rates for different investments.

commercial activities. Similar usage of hurdle rates can among others be found in the POLES model [68], the NEMS model [40], the ReEDS model [84] and the PowerACE-Europe model [148]. As proposed by Goulder and Williams [178], it is also possible to simulate the decisions of private agents using finance-equivalent discount rates in a first stage, and subsequently evaluate the resulting outcome from a societal perspective using a social discount rate. This is also the approach used in the PRIMES model [38].

6.1.2 Strengths and limitations of optimization models

Optimization models have the main advantage that they can rely on fast and efficient solvers to study model instances with the required large geographical, temporal and sectoral scope [51, 179, 180]. Recently, this has become increasingly relevant because a higher level of temporal, technical and spatial detail is required to properly account for the challenges related to the massive integration of intermittent renewables [181, 47].

However, there are limits to the applicability of optimization models to compute the equilibrium. One of these limits is that optimization models implicitly assume price-taking agents, and therefore are not suited to determine the equilibrium if certain agents behave strategically (e.g., GenCos exercising market power in an oligopoly). For analyzing the equilibrium in imperfectly competitive markets, other mathematical techniques to formulate equilibrium problems, such as mixed complementarity problems (MCPs), mathematical problems with equilibrium constraints (MPECs) and equilibrium problems with equilibrium constraints (EPECs) are required (see e.g., [182, 80, 109, 183] for examples analyzing the impact of different degrees of market power on the long-run equilibrium). For a detailed description of these mathematical techniques, we refer to [96]. While the limitation of assuming perfectly competitive (i.e., price-taking) agents in optimization models is well known, there are other, less commonly known, limitations which restrict the use of optimization models for computing the equilibrium. More specifically, optimization models cannot directly represent certain market designs, policy interventions and assumptions regarding the behavior of agents.

To the best of our knowledge, there is no general overview of the limitations of optimization models, and the corresponding implications for determining the equilibrium in deregulated competitive but imperfect energy markets. In the literature, these limitations are typically mentioned on a case-by-case basis when such a limitation is encountered for the specific problem at hand. An example here is the determination of the long-run equilibrium under different emission allowance allocation rules for which different authors have developed an MCP to overcome the limitations of optimization models [184, 185]. Other cases can be found in [186] and [72], where an MCP and an iterative algorithm were developed, for analyzing the impact of introducing average cost pricing for a consortium of large industrial consumers and the impact of feed-in tariffs for renewables, respectively. Moreover, in the papers referenced above, typically little information is provided as to why the problem at hand cannot be simulated using an optimization model. One exception is the paper of Murphy et al. [187], which provides a high-level non-mathematical overview of the limitations of optimization models. However, due to the fact that a non-mathematical approach is taken, certain aspects are overly simplified.

6.2 Optimization and equilibrium

This section provides some background regarding the use of optimization models to compute the market equilibrium. This section is mainly intended for readers not having a background in economics.

6.2.1 Competitive equilibrium and surplus maximization

In this section, we provide two distinct ways of finding the competitive equilibrium under the assumption of price-taking producers and consumers. The first approach starts from an explicit description of different agents, each facing their own optimization problem (here, producers aiming to maximize their producer surplus (PS) and consumers aiming to maximize their consumer surplus (CS)). The conditions which must be satisfied at the optimum of each agent's optimization problem (i.e., the optimality conditions) will be derived. The equilibrium can then be found by solving the set of optimality conditions of the optimization problems of all agents involved. The second approach starts by defining a total surplus function and finds the equilibrium by directly optimizing (i.e., maximizing) this function. As such, this section aims to show that total surplus is maximized in the competitive equilibrium (at least under certain conditions). As we will more formally illustrate in Section 6.3, the first approach strongly relates to the methodology of solving an equilibrium problem using MCPs, whereas the latter approach is the one adopted in optimization problems. It is relevant to note that the first approach starts from the optimization problem of individual agents, and is therefore not bounded to price-taking agents, whereas the total surplus maximization approach implicitly assumes agents are price takers.

Consider the equilibrium between a number of price-taking producers and consumers. The consumers are represented by their aggregate inverse demand function $f_d^{-1}(q)$, and the producers are represented by an inverse supply function $f_s^{-1}(q)$. For any given price p, produced and consumed quantities q_p and q_c, the PS and the CS can be stated as follows:

$$CS(p, q_c) = \int_0^{q_c} f_d^{-1}(q_c')dq_c' - pq_c \tag{6.1}$$

$$PS(p, q_p) = pq_p - \int_0^{q_p} f_s^{-1}(q_p')dq_p' \tag{6.2}$$

The equilibrium can be described mathematically by considering the optimality conditions for each actor's optimization problem. For a given price, the consumers will decide on the quantity to consume which maximizes the CS. A necessary condition for the optimal quantity consumed is that $\frac{\partial CS(p,q_c)}{\partial q_c} = 0$, and hence, $f_d^{-1}(q_c) = p$, i.e., consumers will consume electricity up to the point where their willingness to pay for an additional unit of consumption equals the market price. Similarly, for a given price the producers will decide upon the quantity to produce which maximizes the aggregated PS. Again, the condition which must be fulfilled in the optimum is that $\frac{\partial PS(p,q_p)}{\partial q_p} = 0$, and hence, $f_s^{-1}(q_p) = p$, i.e., producers will produce up to the point where the price equals the marginal production cost. Finally, it must be considered that in the equilibrium the produced and consumed quantities should be balanced, i.e., $q_p = q_c$. The equilibrium can thus be described by the following set of equations:

$$f_d^{-1}(q_c) = p,$$

$$f_s^{-1}(q_p) = p,$$

$$q_p = q_c,$$

which can be reduced to: $p^* = f_d^{-1}(q^*) = f_s^{-1}(q^*)$, where p^* and q^* respectively represent the equilibrium price and quantity. This is visualized in Fig. 6.1.

From a centralized perspective, the TS, i.e., the sum of the CS and the PS can be formulated as follows:

$$TS(q) = \int_0^{q} f_d^{-1}(q')dq' - \int_0^{q} f_s^{-1}(q')dq' \tag{6.3}$$

Here, it is directly considered that the produced and consumed quantities should be identical. The first term in the above equation reflects the consumer value whereas the last term reflects the production costs. At the point of maximum

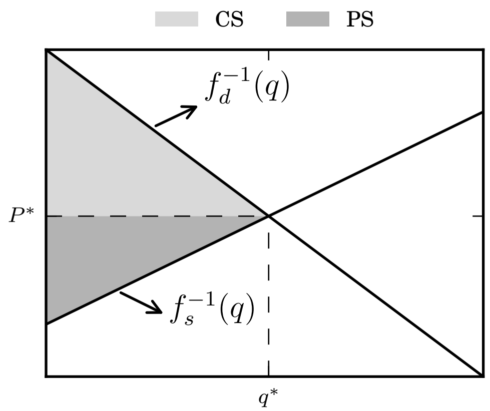


Figure 6.1: Total surplus is maximized in a competitive equilibrium.

surplus, $\frac{dTS(q)}{dq} = 0$, and hence $f_d^{-1}(q^*) = f_s^{-1}(q^*)$, which describes the same equilibrium as the one found above. As such, this example illustrates that in the competitive equilibrium, the TS is maximized. Therefore, it is possible to rely on surplus maximization models to compute the market equilibrium in competitive markets with price-taking actors (at least under certain conditions).

6.2.2 Imperfect markets: surplus maximization versus social welfare maximization

Optimization models rely on surplus maximization for both determining the welfare maximizing solution (normative perspective) and for analyzing the market equilibrium (descriptive perspective). In this regard, the terms total surplus and social welfare are frequently used interchangeably, and optimization models are correspondingly referred to as welfare maximization models (see e.g., [96]). This corresponds to the prevalent idea that optimization models reflect perfect competition (see e.g., [187, 51, 97]). Note that to ensure perfect competition, several conditions must be satisfied, of which price-taking behavior is only one. Other conditions include, among others, the lack of externalities, no barriers to entry or exit and no government intervention. In this section, we argue that maximization of total surplus does not necessarily reflect all conditions needed for perfect competition. The implications are that (i) not all surplus maximization models are welfare maximization models and (ii) surplus maximization models can be used to compute the equilibrium in imperfect but competitive markets (at least in some cases).

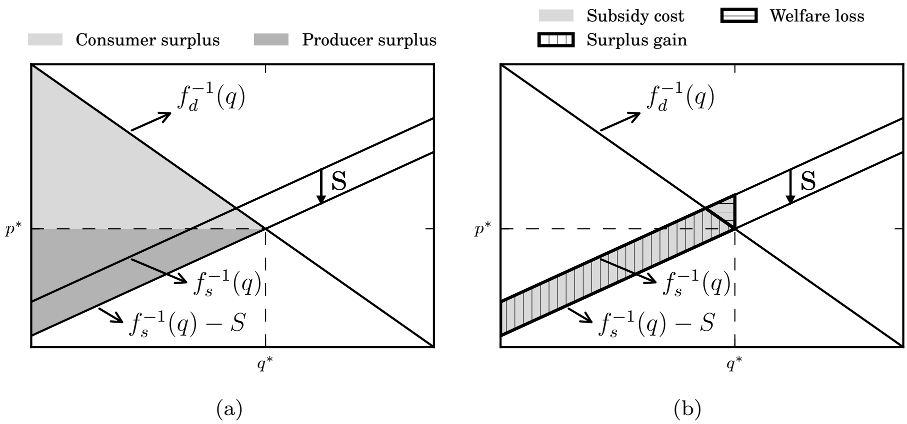


Figure 6.2: Impact of a subsidy S for the supply side on the total surplus and the social welfare.

Consider as an example a competitive market where a subsidy S is introduced for the supply side. For simplicity, we consider here that the entire supply side receives the same subsidy per unit of output. More commonly, specific technologies are targeted, e.g., subsidies for renewable technologies. As illustrated in Fig. 6.2, this subsidy will alter the supply curve, leading to a different equilibrium. This equilibrium is again found where both the producers and the consumers have maximized their surplus, as visualized in Fig. 6.2a. The introduction of the subsidy allows both the consumers and the producers to increase their surplus, and hence, the total surplus also increases (as highlighted by the area with the vertical lines in Fig. 6.2b). However, from a societal perspective, the introduction of the subsidy also involves a cost which equals q^*S (visualized by the grey area in Fig. 6.2b). Under the assumption that there are no other market distortions, Fig. 6.2b shows that the gain in TS does not completely offset the subsidy cost, and hence that the introduction of the subsidy results in a welfare loss (visualized by the area with the horizontal lines).

Depending on whether the optimization model is used for maximizing the social welfare or determining the market equilibrium, the objective function to be maximized and the constraints might differ. For the simple example presented above, the objective function of the surplus maximization model is:

$$TS(q) = \int_0^q f_d^{-1}(q')dq' - \int_0^q \big((f_s^{-1}(q') - S\big)dq' \qquad (6.4)$$

, where $f_s^{-1}(q)$ is the original inverse supply function and S represents the subsidy level. In contrast, one can easily derive for this example that every subsidy would have a negative impact on the social welfare, and hence that the point of maximum social welfare is found in the equilibrium that would have been found in the absence of the subsidy. Hence, the objective function of the social welfare maximization model is again as in Eq. (6.3):

$$TS(q) = \int_0^q f_d^{-1}(q')dq' - \int_0^q f_s^{-1}(q')dq' \qquad (6.5)$$

More generally, if the optimization model is used to compute the solution which maximizes social welfare (i.e., a normative perspective is taken), abstraction should be made from market imperfections such as subsidies, taxes, non-internalized externalities, barriers to entry, imperfect information, etc. In contrast, if an optimization model is used to compute the market equilibrium (i.e., a descriptive perspective is taken), the model should represent the markets one wants to analyze as closely as possible, including market distortions.

Although not all market distortions can be represented in an optimization model, the use of optimization models is far but restricted to markets with perfect competition. We focus on the limitations of representing certain market distortions in Section 6.3.2 whereas we mention some of the market distortions which can be accounted for in optimization models in Section 6.3.3.

6.3 Limitations and possibilities for determining the market equilibrium using optimization models

In the previous section, we have shown that the total surplus is maximized in the equilibrium found in perfectly competitive markets, and hence that optimization models can be used to compute this equilibrium. Additionally, we have illustrated that the use of optimization models for computing the economic equilibrium is not restricted to markets that fulfill all conditions of perfect competition. However, as specified in Section 6.1, there are limitations to using optimization models to compute the equilibrium when specific market designs, policy interventions and/or behavioral characteristics of agents are introduced. This section aims to expose these limitations of optimization models.

To expose the limitations of optimization models, we rely on the fact that (i) mixed complementarity problems (MCPs) are used frequently to solve equilibrium problems and (ii) MCPs generalize the class of linear and non-linear optimization problems with continuous variables. The latter implies that every linear or non-linear optimization problem with continuous variables can be converted to an MCP, but the opposite does not hold. If a certain MCP describing an economic equilibrium cannot be derived by converting an optimization problem to its corresponding MCP, we can conclude that this equilibrium cannot be computed directly by solving an optimization model. By analyzing how an optimization problem and an equilibrium problem are converted to an MCP, we will show that certain conditions need to be fulfilled in order for an optimization problem to be able to compute the equilibrium. These mathematical conditions can then be interpreted from an economic/market perspective. We restrict ourselves here to equilibrium problems with price-taking agents which can be formulated as an MCP[3].

The remainder of this sections is as follows: first Section 6.3.1 illustrates for a simplified example of a generation expansion planning problem how the equilibrium problem can be formulated as an MCP and how an optimization problem can be converted to an MCP. Next, Section 6.3.2 analyzes which conditions must be fulfilled in order for an equilibrium problem to be casted in an optimization problem and the corresponding limitations for the use of optimization models for solving equilibrium problems. Finally, Section 6.3.3 briefly highlights the equilibrium problems which can be solved using optimization models.

6.3.1 Generation expansion planning problem

Problem formulation

Equilibrium problem Consider multiple price-taking GenCos i participating in a wholesale market. To simplify the problem, assume that each GenCo has the option to invest in generation capacity cap_i of a single technology, which is characterized by an annualized investment cost C_i^{INV} and a constant generation cost VC_i. This generation capacity can be used to generate a power output $gen_{i,t}$ during every time step t (having a duration Δ_t) within the year. The generated electric energy can be sold in the market at a price p_t^{el}. The demand

[3]Not every equilibrium problem can be formulated as an MCP. Certain type of equilibria, such as Stackelberg equilibria, cannot be formulated as an MCP. Since MCPs generalize the group of non-linear optimization problems with continuous variables, these equilibria can also not be solved directly using a non-linear optimization problem with continuous variables. Stackelberg equilibria are commonly formulated as MPECs or EPECs and are often used to model the strategic behavior of an agent which anticipates the reaction of other agents when determining his own actions. These types of equilibria are out of the scope of this work.

side in each time period t is represented by a given inverse demand function $f_{d,t}^{-1}(q_t)$. Here, the equilibrium problem is to find the long-run equilibrium.

In this example, each GenCo i faces the problem of determining the investment and operational decisions which maximize its long-run profits subject to (s.t.) certain constraints[4]:

$$\max_{cap_i, gen_{i,t}} \quad \sum_t (gen_{i,t} p_t^{el} \Delta_t) - \left(cap_i C_i^{INV} + \sum_t (gen_{i,t} VC_{i,t} \Delta_t)\right) \tag{6.6a}$$

$$s.t. \quad cap_i - gen_{i,t} \geq 0 \quad (\gamma_{i,t}) \quad \forall t \tag{6.6b}$$

$$gen_{i,t} \geq 0 \quad \forall t \tag{6.6c}$$

$$cap_i \geq 0 \tag{6.6d}$$

In addition, the consumers aim to maximize their consumer surplus:

$$\max_{q_t} \quad \sum_t \left(\int_0^{q_t} f_{d,t}^{-1}(q_t') dq_t' \Delta_t\right) - \sum_t (p_t^{el} q_t \Delta_t) \tag{6.7a}$$

$$s.t. \quad q_t \geq 0 \quad \forall t \tag{6.7b}$$

$$\tag{6.7c}$$

Finally, the linking constraints need to be considered. These linking constraints are constraints which link together the variables of the different optimization problems (and thus the decision variables of the different agents). Typically, these are constraints which ensure that there is a balance between supply and demand, and are therefore sometimes referred to as market clearing constraints. Aside from ensuring a balance between the demand and supply of certain commodities, linking constraints are also frequently used to reflect the scarcity of certain commodities or reflect policy constraints which cap the total consumption/production of certain commodities. In this example, we only consider the balance between the supply and demand of electricity:

$$\sum_i gen_{i,t} \Delta_t = q_t \Delta_t \quad \forall t \tag{6.8}$$

MCP formulation To derive the MCP formulation of the equilibrium problem, the Karush-Kuhn-Tucker (KKT) conditions of each optimization problem need

[4] Note that we consider both producers and consumers to be price takers. The price-taking behavior follows from the fact that the price p_t^{el} enters as a parameter in their respective optimization problems, i.e., although the price depends on the agents' decisions and hence is an endogenous variable of the equilibrium problem, within each agent's optimization problem, the price is considered to be a parameter which is independent from its own decisions.

to be determined. These KKT conditions are a set of equations and inequalities which form a mathematical expression of the necessary conditions for the optimal solution of an optimization problem. Under certain conditions, these KKT conditions are also sufficient. For instance, for linear and convex quadratic optimization problems, the KKT conditions are both necessary and sufficient, which means that any solution which satisfies the KKT conditions is effectively an optimal solution of the optimization problem[5] [96]. By combining the KKT conditions of all optimization problems and adding the linking constraints, the MCP formulation of the equilibrium problem is derived. This MCP formulation of the equilibrium problem is thus nothing else than a set of equations and inequalities which must be fulfilled in the equilibrium. These equations and inequalities consist of conditions which must be satisfied in order for the solution to reflect the optimal decision making of the agents involved, conditions which reflect the constraints faced by each agent, and the linking constraints. Such an MCP can be solved using commercial solvers, such as the PATH solver [96].

The MCP of the generation expansion problem is shown below. Here, we make use of the perpendicular operator $\perp$. The presence of the perpendicular operator between two inequalities $g(x) \leq 0$ and $\alpha \geq 0$ represents an additional equation stating that at least one of the inequalities should be an equality, i.e., $g(x)\alpha = 0$.

$$p_t^{el}\Delta_t \leq VC_{i,t}\Delta_t + \gamma_{i,t} \quad \perp \quad gen_{i,t} \geq 0 \qquad \forall i,t \tag{6.9a}$$

$$\sum_t (\gamma_{i,t}) \leq C_i^{INV} \quad \perp \quad cap_i \geq 0 \qquad \forall i \tag{6.9b}$$

$$cap_i - gen_{i,t} \geq 0 \quad \perp \quad \gamma_{i,t} \geq 0 \qquad \forall i,t \tag{6.9c}$$

$$f_{d,t}^{-1}(q_t) \leq p_t^{el} \quad \perp \quad q_t \geq 0 \qquad \forall t \tag{6.9d}$$

$$\sum_i gen_{i,t}\Delta_t = q_t\Delta_t \qquad \forall t \tag{6.9e}$$

Eq. (6.9a)-(6.9c) represent the KKT conditions of the GenCos, Eq. (6.9d) is the KKT condition for the consumer and Eq. (6.9e) is a linking constraint which enforces a balance in the generation and consumption of the commodity electricity. From Eq. (6.9a), we can derive that when a certain agent i decides to generate electricity using a certain technology, the price should be at least as high as the generation cost of that technology. If this is not the case, the generator will decide not to generate electricity. Moreover, from Eq. (6.9c) and

[5] For certain type of problems, such as (mixed) integer programs, the KKT conditions are not meaningful, i.e., the KKT conditions are not necessary conditions for the optimal solution. The inability to represent integer variables is a main limitation of MCPs [96].

Eq. (6.9a), we can deduce that if a technology is generating electricity, but less than its installed capacity, this plant clears the market, and hence, the price equals the generation cost of that technology[6]. When a technology is generating at maximal capacity, the price can be higher than the generation cost of that technology, and the owners of the plants of that technology can earn infra-marginal rents (indicated by the dual variable $\gamma_{i,t}$). In terms of investments, we can see from Eq. (6.9b) that an agent will only invest in capacity of a certain technology if the infra-marginal rents that would be earned during the different time steps are sufficient to cover the investment costs. Moreover, when an agent invests in a certain technology, it will do so up to the point where the infra-marginal rents are just sufficient to cover the investment costs. From Eq. (6.9d), it follows that the consumers consume up to the point where the inverse demand function, i.e., their willingness to pay, equals the electricity price.

Optimization problem formulation Considering the same GenCos and consumers, the solution yielding maximal total surplus is the solution to the following optimization problem:

$$\max_{q_t, cap_i, gen_{i,t}} \quad \sum_t \Big(\int_0^{q_t} f_{d,t}^{-1}(q_t')dq_t'\Delta_t \Big) - \sum_i \Big(cap_i C_i^{INV} + \sum_t (gen_{i,t} VC_i \Delta_t) \Big) \tag{6.10a}$$

$$s.t. \quad cap_i - gen_{i,t} \geq 0 \quad (\gamma_{i,t}) \quad \forall i, t \tag{6.10b}$$

$$gen_{i,t} \geq 0 \quad \forall i, t \tag{6.10c}$$

$$cap_i \geq 0 \quad \forall i \tag{6.10d}$$

$$q_t \geq 0 \quad \forall t \tag{6.10e}$$

$$\sum_i gen_{i,t}\Delta_t = q_t\Delta_t \quad (\lambda_t) \quad \forall t \tag{6.10f}$$

This optimization problem can be solved directly using efficient optimization solvers. However, to illustrate the equivalence between the solution of the optimization problem (6.10) and the MCP formulation of the equilibrium problem (6.9), we will convert the above optimization problem (6.10) to an MCP via its KKT conditions. Note that in this case, there is only a single optimization problem and therefore the linking constraints are internal constraints of this

[6]In this example, we do not consider the need for ancillary services such as spinning reserve requirements, and the corresponding interest to operate plants below the rated capacity in order to be able to provide these services.

optimization problem. Hence, the MCP formulation of the surplus maximization problem is simply the set of KKT conditions of the surplus maximization problem, i.e.:

$$\lambda_t \Delta_t \leq VC_{i,t} \Delta_t + \gamma_{i,t} \quad \perp \quad gen_{i,t} \geq 0 \qquad \forall i,t \tag{6.11a}$$

$$\sum_t (\gamma_{i,t}) \leq C_i^{INV} \quad \perp \quad cap_i \geq 0 \qquad \forall i \tag{6.11b}$$

$$cap_i - gen_{i,t} \geq 0 \quad \perp \quad \gamma_{i,t} \geq 0 \qquad \forall i,t \tag{6.11c}$$

$$f_{d,t}^{-1}(q_t) \leq \lambda_t \quad \perp \quad q_t \geq 0 \qquad \forall t \tag{6.11d}$$

$$\sum_i gen_{i,t} \Delta_t = q_t \Delta_t \qquad \forall t \tag{6.11e}$$

For the presented example, by noting that the dual variable of the market clearing condition (Eq. (6.10f)) of the optimization problem represents the equilibrium price (i.e., $\lambda_t = p_t^{el}$), it becomes clear that the MCPs (6.11) and (6.9) are equivalent. Hence, instead of having to solve the MCP, a faster computation of the equilibrium is possible by simply solving the optimization problem (problem (6.10)) [96, 180, 187]. Both approaches to solving the equilibrium problem are schematically represented in Fig. 6.3.

As stated earlier, any non-linear optimization problem with continuous variables can be converted to an MCP via its KKT conditions, but it will not always be possible to formulate an optimization problem of which the optimal solution represents the equilibrium [96, 187]. More specifically, when we stated earlier that an optimization model cannot be used to compute the equilibrium in certain circumstances, we mean that it is not possible to formulate an optimization problem such that the KKT conditions of this optimization problem correspond to the MCP formulation of the equilibrium[7].

[7] Although it might not be possible to formulate an optimization problem such that the KKT conditions of this optimization problem are identical to the MCP formulation of the equilibrium, it can be possible to determine the equilibrium via iterative algorithms in which the optimization model is solved repeatedly and parameters are adapted. Such iterative algorithms have been used frequently [187] (see e.g., [72, 51] for recent examples). However, the need to solve the optimization problem repeatedly leads to high computational costs. In addition, these iterative algorithms might face convergence issues [51]. A detailed discussion of such iterative algorithms and other solution techniques for equilibrium problems are out of the scope of this chapter.

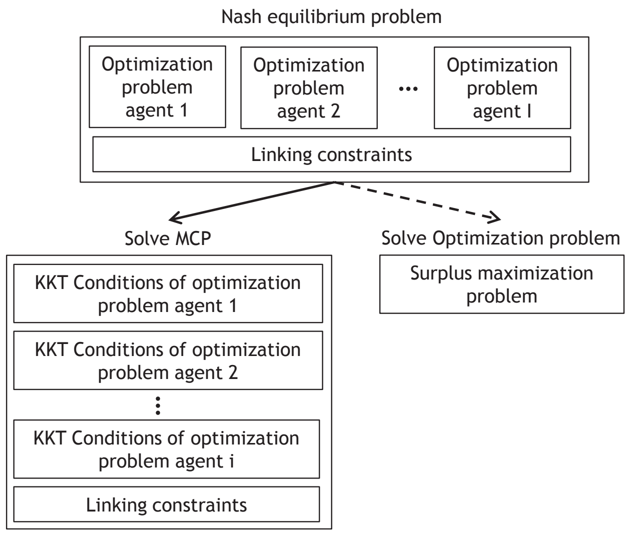


Figure 6.3: Schematic of different approaches to solving a Nash equilibrium problem. The dashed arrow indicates that not all equilibrium problems which can be formulated as a mixed complementarity problem (MCP) can be solved by solving a single optimization model.

A closer look at the equivalence

To gain insights into the limitations of optimization models, it is relevant to have a further look at how the surplus maximization problem (problem (6.10)), via its KKT conditions, leads to the same MCP as the MCP formulation of the equilibrium problem.

In this regard, it is of interest to observe that in the presented generation expansion problem, the KKT conditions of the surplus maximization problem comprise the KKT conditions of each individual agent's optimization problem. The KKT conditions of each agent's optimization problem reflect both the constraints faced by each agent and the conditions for the optimal decision making of each agent. The conditions for the optimal decision making in turn consist of three types of terms: costs/revenue terms related to participation in the markets for which the prices are endogenously determined (i.e., the endogenous markets), terms related to exogenously specified costs/revenues and terms related to the shadow prices of the agent's constraints. Applied to the KKT conditions of the GenCo in the generation expansion planning problem (Eq. (6.9a)-(6.9c)), Eq. (6.9c) reflects the constraint faced by the agent and Eq. (6.9a)-(6.9b) reflect the conditions for optimally deciding on the power generation in each time step and the installed capacity respectively. In these conditions for optimal decision making, the term $p_t^{el}\Delta_t$ reflects the revenues from participating in the electricity market, the terms $VC_{i,t}\Delta_t$ and FC_i are exogenously specified production and investment costs, and $\gamma_{i,t}$ are the infra-marginal rents related to the capacity constraint.

As shown in the example above, a surplus maximization problem directly integrates both the agents' constraints[8] (Eq. (6.10b)-(6.10e)) and the exogenously specified cost/revenue components (the terms $cap_i C_i^{INV} + \sum_t (gen_{i,t} VC_i \Delta_t)$ in Eq. (6.10a)). Hence, the corresponding terms will appear identically in the KKT conditions of the surplus maximization problem as in the KKT conditions of the agent's optimization problem.

The main difference relates to the terms reflecting the revenues/costs from the participation in the endogenous markets. These revenue/cost terms related to the endogenous markets are explicitly represented in the objective function of each agent's optimization problem (see e.g., the term $\sum_t (gen_{i,t} p_t^{el} \Delta_t)$ in Eq. (6.6)) and hence appear in the KKT conditions of the agents optimization problem. In contrast, in the surplus maximization problem (6.10), no revenue or cost terms related to endogenous markets are specified[9]. Nevertheless, the KKT conditions of the surplus maximization problem also contain these terms. This is because the cost or revenue terms related to the endogenous markets now appear indirectly in the KKT conditions of the surplus maximization problem via the linking constraints.

Each linking constraint integrated in a surplus maximization problem will thus indirectly describe a market, i.e., both the price (dual variable of the linking constraint) and the variables receiving/having to pay this price are indirectly specified via the linking constraints. In the example above, the linking constraint ensuring a balance between the supply and demand of electricity indirectly specifies that every unit of electricity generated in time step t, i.e., $gen_{i,t}\Delta_t$, receives a payment λ_t. Similarly, every unit of electricity consumed in time step t requires a payment of λ_t.

The information presented above is summarized in Fig. 6.4 and Fig. 6.5 which schematically illustrate how the MCP formulation of an equilibrium problem and the MCP formulation of a surplus maximization problem is formed respectively.

[8] If this is not the case, the solution to the optimization problem might violate the constraints faced by one or more agents. In this case, the solution of the optimization problem cannot be a solution to the equilibrium problem.

[9] Recall that the objective function of the surplus maximization problem consists of the total surplus, which is constructed of the consumer value minus the production costs.

In addition, Fig. 6.6 gives a mathematical overview of the generic structure of an optimization problem and an equilibrium problem and how both are cast to an MCP.

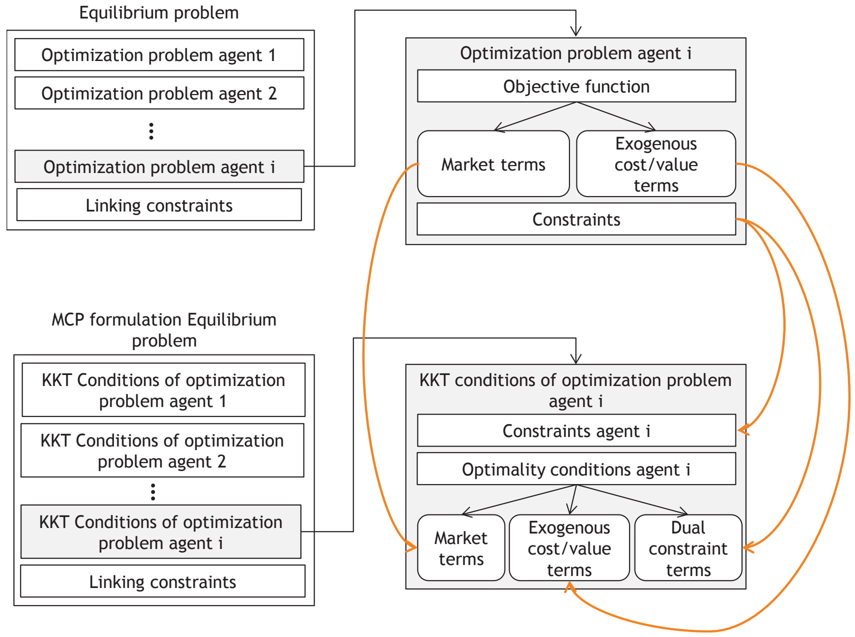


Figure 6.4: Schematic of how the mixed complementarity problem (MCP) formulation of an equilibrium problem is formed.

6.3.2 Limitations of optimization models

Limitations related to duality

A first set of limitations of optimization problems is related to duality. In the previous section, we have shown that all revenues and cost terms related to the endogenous markets appear in the MCP derived from the surplus maximization problem indirectly via the linking constraints and the corresponding dual variables. These linking constraints thus not only represent physical or policy constraints of the optimization problem, but also specify the remuneration in the markets implicitly formed around each of these constraints. As such, optimization models cannot distinguish between a physical or policy constraint on the one hand and the revenues and costs attached to the variables appearing

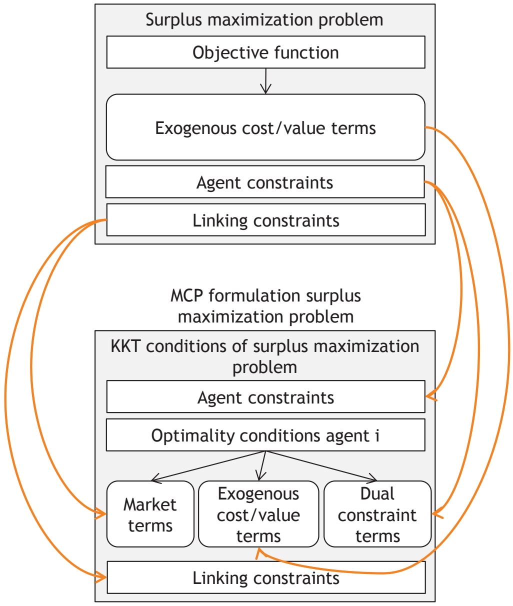


Figure 6.5: Schematic of how the mixed complementarity problem (MCP) formulation of a surplus maximization problem is formed.

in this constraint via the market implicitly formed around this constraint on the other hand. This leads to three assumptions which are inherently made in optimization models and are listed below:

1. all agents' variables contributing to a certain linking constraint participate in a paid-as-cleared market implicitly formed around this linking constraint. This implicitly formed market provides a unique endogenously determined price (the dual variable of that linking constraint) which applies to all variables contributing to that linking constraint[10];

2. the endogenously determined market price does not directly influence the value of variables not appearing in the corresponding linking constraint;

[10]Note that this does not imply that all variables contributing equally to a certain linking constraint should get the same remuneration/cost in total. This because these variables can get additional value (either by appearing in other linking constraints or via exogenously specified costs/revenue terms) which might not be the same for different variables. E.g., certain technologies can get a fixed subsidy on top of their revenues from selling their electricity in the market.

Surplus maximization problem

$$Max_{\mathbf{x}} \quad F(\mathbf{x})$$

s.t.:

$$g_i^{n_i}(\mathbf{x}_i) \geq 0 \quad (\alpha_i^{n_i}) \quad \forall i = 1,\ldots,I \quad n_i = 1,\ldots,N_i$$

$$\mathbf{x} \geq 0$$

$$v^1(\mathbf{x}) \geq 0 \quad (\gamma^1)$$

$$\vdots$$

$$v^M(\mathbf{x}) \geq 0 \quad (\gamma^M)$$

Equilibrium problem

Optimization problem

Agent 1

$$Max_{\mathbf{x}_1} \quad \theta_1(\mathbf{x}_1, \gamma)$$

s.t.:

$$g_1^1(\mathbf{x}_1) \geq 0 \quad (\alpha_1^1)$$

$$\vdots$$

$$g_1^{N_1}(\mathbf{x}_1) \geq 0 \quad (\alpha_1^{N_1})$$

$$\mathbf{x}_1 \geq 0$$

$\cdots$

Optimization problem

Agent I

$$Max_{\mathbf{x}_I} \quad \theta_I(\mathbf{x}_I, \gamma)$$

s.t.:

$$g_I^1(\mathbf{x}_I) \geq 0 \quad (\alpha_I^1)$$

$$\vdots$$

$$g_I^{N_I}(\mathbf{x}_I) \geq 0 \quad (\alpha_I^{N_I})$$

$$\mathbf{x}_I \geq 0$$

$$v^1(\mathbf{x}) \geq 0 \quad \perp \quad \gamma^1 \geq 0$$

$$\vdots$$

$$v^M(\mathbf{x}) \geq 0 \quad \perp \quad \gamma^M \geq 0$$

MCP formulation of the surplus maximization problem

$$\frac{\partial F(\mathbf{x})}{\partial \mathbf{x}_1} + \sum_{n_1=1}^{N_1} \alpha_1^{n_1} \frac{\partial g_1^{n_1}(\mathbf{x}_1)}{\partial \mathbf{x}_1} + \sum_{m=1}^{M} \gamma^m \frac{\partial v^m(\mathbf{x})}{\partial \mathbf{x}_1} \leq 0 \quad \perp \quad \mathbf{x}_1 \geq 0$$

$$\vdots$$

$$\frac{\partial F(\mathbf{x})}{\partial \mathbf{x}_I} + \sum_{n_I=1}^{N_I} \alpha_I^{n_I} \frac{\partial g_I^{n_I}(\mathbf{x}_I)}{\partial \mathbf{x}_I} + \sum_{m=1}^{M} \gamma^m \frac{\partial v^m(\mathbf{x})}{\partial \mathbf{x}_I} \leq 0 \perp \quad \mathbf{x}_I \geq 0$$

$$g_i^{n_i}(\mathbf{x}_i) \geq 0 \quad \perp \quad \alpha_i^{n_i} \geq 0 \quad \forall i = 1,\ldots,I \quad n_i = 1,\ldots,N_i$$

$$v^1(\mathbf{x}) \geq 0 \quad \perp \quad \gamma^1 \geq 0$$

$$\vdots$$

$$v^M(\mathbf{x}) \geq 0 \quad \perp \quad \gamma^M \geq 0$$

MCP formulation of the equilibrium problem

$$\frac{\partial \theta_1(\mathbf{x}_1, \gamma)}{\partial \mathbf{x}_1} + \sum_{n_1=1}^{N_1} \alpha_1^{n_1} \frac{\partial g_1^{n_1}(\mathbf{x}_1)}{\partial \mathbf{x}_1} \leq 0 \quad \perp \quad \mathbf{x}_1 \geq 0$$

$$\vdots$$

$$\frac{\partial \theta_I(\mathbf{x}_I, \gamma)}{\partial \mathbf{x}_I} + \sum_{n_I=1}^{N_I} \alpha_I^{n_I} \frac{\partial g_I^{n_I}(\mathbf{x}_I)}{\partial \mathbf{x}_I} \leq 0 \quad \perp \quad \mathbf{x}_I \geq 0$$

$$g_i^{n_i}(\mathbf{x}_i) \geq 0 \quad \perp \quad \alpha_i^{n_i} \geq 0 \quad \forall i = 1,\ldots,I \quad n_i = 1,\ldots,N_i$$

$$v^1(\mathbf{x}) \geq 0 \quad \perp \quad \gamma^1 \geq 0$$

$$\vdots$$

$$v^M(\mathbf{x}) \geq 0 \quad \perp \quad \gamma^M \geq 0$$

Figure 6.6: Schematic of a surplus maximization problem and an equilibrium problem and how these problems are cast to a mixed complementarity problem (MCP). The equilibrium problem consists of I agents all facing their own optimization problem. The decision variables of agent i are represented by the vector $\mathbf{x}_i$. Assuming price-taking agents, the objective function θ_i of an agent i is dependent on the agents decision variables and the vector of prices $\boldsymbol{\gamma}$ which are the dual variables of the M linking constraints. Each agent i faces a number N_i of constraints. The objective function of the surplus maximization problem is dependent on the decision variables of all agents (denoted by $\mathbf{x}$).

3. all agents have the same valuation of the revenues or costs related to the participation in a certain market formed around a linking constraint.

In addition, optimization problems cannot contain dual variables in the primal problem formulation and can therefore not represent constraints of agents which contain endogenously determined market prices. This leads to a fourth assumption inherently made in optimization models:

4. the decision space of each agent is not dependent on the endogenously determined market prices[11].

If an equilibrium problem violates one of the above assumptions, the equilibrium problem cannot be directly solved using an optimization model. These inherent assumptions hence restrict the use of optimization models for solving equilibrium problems.

The inherent assumptions 1-3 are mathematically expressed in the following condition:

Condition 1: A necessary condition for an equilibrium problem to be cast in a linear or non-linear optimization model with continuous variables is that for each agent i in the equilibrium problem, the objective function $\theta_i(\mathbf{x}_i, \boldsymbol{\gamma})$ of its respective optimization problem can be formulated as:

$$\theta_i(\mathbf{x}_i, \boldsymbol{\gamma}) = F(\mathbf{x}) + \sum_{m=1}^{M} \gamma^m v^m(\mathbf{x}) + a_i(\mathbf{x}_{-i}, \boldsymbol{\gamma}) \quad \forall i, \tag{6.12}$$

where $\mathbf{x}_i$ and $\mathbf{x}_{-i}$ are respectively the decision variables of agent i and the decision variables of all agents except agent i. The decision variables of all agents are indicated by $\mathbf{x}$. Finally, $v^m(\mathbf{x})$ represents the m^{th} linking constraints of the equilibrium problem with corresponding price γ^m.

If a function $F(\mathbf{x})$ and functions $a_i(\mathbf{x}_{-i}, \boldsymbol{\gamma})$ can be found such that the above condition is satisfied for all agents i, the function $F(\mathbf{x})$ is the objective function of the optimization problem of which the optimal solution represents the equilibrium.

[11] As discussed in Section 6.3.1 presenting the generation expansion planning problem, the optimal decisions of an agent are dependent on the outcome of the markets (e.g., a generator will not decide to generate electricity unless the price of electricity covers at least its generation costs). However, the decision space of each agent, i.e., the feasible area of its optimization problem, in the presented example is independent of the market prices.

This condition shows that in order for an equilibrium problem to be cast into a surplus maximization problem (or by extension, any non-linear optimization problem with continuous variables), the terms containing endogenously determined market prices in the objective function of each agent must correspond to a strict format which relates to the linking constraints.

For instance, in the generation expansion planning problem presented in Section 6.3.1, we had only a single linking constraint, which was of the form $\sum_i gen_{i,t}\Delta_t - q_t\Delta_t = 0$ and of which the dual variable represented the price of electricity p_t^{el}. Hence, according to the condition (Eq. (6.12)), the objective function of each GenCo should contain a term $p_t^{el} gen_{i,t}\Delta_t$ and no other terms containing a product of p_t^{el} and one of the GENCO's decision variables. Similarly, the objective function of the consumer should contain a term $-p_t^{el} q_t\Delta_t$ and no other terms containing a product of p_t^{el} and one of the consumers' decision variables. As can be seen in the objective function of the GenCos and the consumers (Eq. (6.6a) and Eq. (6.7b)), these conditions are fulfilled and hence we were able to compute the equilibrium using a surplus maximization problem.

However, certain market imperfection introduced via the market design or policy interventions will result in markets or agents which deviate from this necessary condition. This is for instance the case when the value of a certain variable is determined outside of the market. For example, a renewable generator receiving a fixed feed-in tariff receives the feed-in tariff rather than the market price for every unit of generated electricity. Nevertheless, the electrical power generated by this renewable generator must enter in the linking constraint since it contributes to meeting the physical constraint requiring a balance between demand and supply and impacts the market. Hence, according to the linking constraint which ensures that there is a balance between the supply and demand of electricity, both the renewable and the non-renewable electricity generation are remunerated via the market price, being the dual variable of the linking constraint.

Another deviation from these assumptions occurs if certain variables are remunerated using certain market prices despite the fact that these variables might not directly participate in this market. Consider as an example a subsidy scheme where investors in renewable generators receive a certain subsidy per unit of installed capacity which is dependent on the market price. In this example, the capacity variable gets some remuneration which is dependent on the electricity price even though the capacity variable does not enter in the linking constraint ensuring the balance between supply and demand of electricity. Finally, also assumptions regarding how agents value the costs and revenues resulting from a certain market can cause deviations from the above conditions. Detailed illustrations of such problems are presented in Section 6.4.

Condition 1 can be derived by demanding that the MCP derived from the surplus maximization problem is identical as the MCP formulation of the equilibrium problem. By assuming that the surplus maximization problem reflects the constraints faced by each agent as well as the physical/policy constraints linking the variables of each agent[12] and using the notation from Fig. 6.6, the following condition must be satisfied in order for both MCPs to be identical[13] (see Fig. 6.6):

$$\frac{\partial F(\mathbf{x})}{\partial \mathbf{x}_i} + \sum_{n_i=1}^{N_i} \alpha_i^{n_i} \frac{\partial g_i^{n_i}(\mathbf{x}_i)}{\partial \mathbf{x}_i} + \sum_{m=1}^{M} \gamma^m \frac{\partial v^m(\mathbf{x})}{\partial \mathbf{x}_i}$$
$$= \frac{\partial \theta_i(\mathbf{x}_i, \boldsymbol{\gamma})}{\partial \mathbf{x}_i} + \sum_{n_i=1}^{N_i} \alpha_i^{n_i} \frac{\partial g_i^{n_i}(\mathbf{x}_i)}{\partial \mathbf{x}_i} \quad \forall i. \tag{6.13}$$

Here, the terms $\sum_{n_i=1}^{N_i} \alpha_i^{n_i} \frac{\partial g_i^{n_i}(\mathbf{x}_i)}{\partial \mathbf{x}_i}$ relate to the constraints faced by agent i and, since these constraints are represented in the agent's optimization problem as well as the surplus maximization problem, thus appear in both the KKT conditions of the surplus maximization problem and the KKT conditions of the optimization problem faced by each agent i. As a result, these terms can be eliminated from the above condition. Eq. (6.13) than reduces to:

$$\frac{\partial F(\mathbf{x})}{\partial \mathbf{x}_i} + \sum_{m=1}^{M} \gamma^m \frac{\partial v^m(\mathbf{x})}{\partial \mathbf{x}_i} = \frac{\partial \theta_i(\mathbf{x}_i, \boldsymbol{\gamma})}{\partial \mathbf{x}_i} \quad \forall i. \tag{6.14}$$

Here, $F(\mathbf{x})$ represents the objective function of the surplus maximization problem. Hence, the term $\frac{\partial F(\mathbf{x})}{\partial \mathbf{x}_i}$ appears in the KKT conditions of the surplus maximization problem via its objective function. In contrast, the terms $\sum_{m=1}^{M} \gamma^m \frac{\partial v^m(\mathbf{x})}{\partial \mathbf{x}_i}$ appear in the KKT conditions of the surplus maximization problem via the linking constraints. Here, γ^m represents the dual variable of linking constraint m and thus reflects the price of a certain implicitly created market. In the MCP of the equilibrium problem, the only remaining terms in the above equation directly follow from the agents' objective functions $\theta_i(\mathbf{x}_i, \boldsymbol{\gamma})$. The agents' objective functions typically directly comprise terms related to the market prices (γ). By integrating both sides of the equation over the decision variables $\mathbf{x}_i$, we finally get the first condition as presented above (Eq. (6.12)).

The fourth inherent assumption/limitation of optimization problems directly follows from the fact that endogenously determined prices are dual variables of

[12]These constraints must be incorporated in the surplus maximization problem to ensure that the optimal solution to this problem is feasible.

[13]Note that this condition must hold for the problem formulation in general, and thus not only at optimality.

the surplus maximization problem, and hence cannot appear in the primal problem formulation[14]. This is more formally presented in the following condition:

Condition 2: A necessary condition for an equilibrium problem to be cast in a linear or non-linear optimization model with continuous variables is that for each agent i in the equilibrium problem, the constraints $g_i^{n_i}$ faced by agent i are not a function of the endogenously determined market prices γ^m.

A straightforward example of a constraint which violates this condition is a constraint imposing a maximum payback time of an investment.

Limitations related to integrability of inverse demand functions

A final limitation of optimization models relates to the use of (econometrically or otherwise defined) analytical expressions for the inverse demand functions. In Section 6.2, we illustrated how the equilibrium in competitive markets can be found by optimizing the total surplus. The total surplus is composed of the consumer value (i.e., utility) subtracted by the production cost. To optimize the total surplus, one thus needs to be able to determine the consumer value and the production cost. The production cost is typically determined bottom-up. However, the consumer value is typically derived by integrating the inverse demand functions[15]. If there are multiple inverse demand functions with cross-price elasticities, the inverse demand functions might not be integrable.

Multiple inverse demand functions with cross-price elasticities may be needed if there are multiple commodities (e.g., a high price for electricity might increase the demand for natural gas) or different time steps (e.g., a high price for electricity in a certain time period might reduce the demand for electricity in this time period but also increase the demand for electricity in subsequent time periods). Typically, energy-system and power-system optimization models consider the demand to be fixed or only consider own-price elasticities. In this case, the consumer value can be easily decomposed into a number of terms, each representing the consumer value for a certain commodity in a certain

[14] From a different perspective, the first limitation can be considered to also directly follow from this fact, since if the objective function of the surplus maximization problem could contain dual variables, this would allow adapting the terms containing endogenously determined prices in the KKT conditions by adding additional terms to the objective function.

[15] Although in principle, the inverse demand functions should be derived from the consumer value or utility function and not vice versa.

time step. Thus, the consumer value function is determined by summing over the integrals of the different inverse demand functions. However, if there are cross-price elasticities, determining the consumer value is less straightforward, and in some cases it is not possible to define a consumer value function such that the optimal solution of the surplus maximization problem reflects the economic equilibrium one would find when assuming certain inverse demand functions. More specifically, it is not possible to formulate such a consumer value function if the inverse demand functions are asymmetric, i.e., the partial derivatives of the inverse demand functions of two commodities to a change in the quantity of the other commodity are not equal. This restricts the option to consider econometrically defined inverse demand functions as these functions rarely satisfy this requirement. A proof based on the derivation presented in [96] is included in Appendix E.

Note that the inability to define the consumer value function also prevents from formulating the optimization problem of consumers, as the consumer surplus is defined as the consumer value subtracted by the costs of acquiring the commodities in the markets. However, instead of deriving the optimality conditions from the consumers' optimization problem and incorporating these in the MCP as was done in the problem presented in Section 6.3.1, one could simply integrate the analytical expressions directly in the MCP (replacing the optimality conditions for the consumers).

We do not focus on this limitation of optimization models in the remainder of this text. For the interested reader, we refer to Gabriel et al. [96] for a more detailed treatment of this limitation of optimization models.

6.3.3 Opportunities for optimization model

Despite the above-mentioned limitations of optimization models for determining the market equilibrium, many markets and market distortions can be simulated using optimization models. In this regard, it is relevant to note that one can easily introduce additional markets (e.g., markets for capacity, ancillary services, renewable energy or greenhouse gas emissions) by introducing additional linking constraints. More specifically, one needs to specify the upper and/or lower bounds for the gross or net consumption of certain commodities or services and how different technologies contribute to meeting these bounds. A recent report developed for the European Commission presents an overview of current market distortions alongside the methodologies which can be used to model these distortions. It turns out that the majority of the distortions listed in this report can be easily modeled using optimization models [188]. Some of these distortions relate to having a non-level playing field (e.g., due to the lack of market access for certain technologies, stringent eligibility criteria or product definitions). To model these distortions, one can easily adapt the variables which can contribute to meeting a certain linking constraint and/or the extent to which different variables can contribute. For example, if storage technologies are not allowed to provide operating reserves, one can simply exclude storage related variables in the linking constraint which imposes the balance between the provision and the requirement for operating reserves. In addition, other distortions listed in this report, such as price-caps and sub-optimal market coupling can be easily simulated using optimization models. In addition, some incomplete markets can be simulated. For example, by considering the electricity balance constraints only on zonal level, zonal pricing (and thus the lack of nodal price signals) can be modeled[16]. Finally, as already indicated before, policy interventions such as volume based instruments (e.g., emission trading schemes or green certificate systems) as well as direct subsidies and taxes (as long as the subsidy or tax is not dependent on the endogenous prices) can be incorporated in optimization models.

6.4 Illustrations

In this section, we illustrate the limitations of optimization models by providing three equilibrium problems related to investments planning which cannot be solved directly using an optimization model. More specifically, we provide an illustration of a policy intervention, a market design and agent behavior which cannot be directly represented in an optimization model. The first illustration addresses the problem of determining the long-run equilibrium when a green certificate scheme is introduced with a guaranteed minimum price for green certificates. The second illustration looks at the problem of determining the long-run equilibrium in generation expansion planning when residential consumers can invest in solar photovoltaic (PV) panels and net metering is applied. Finally, the last illustration addresses several issues related to representing the equilibrium if agents face uncertainty.

While it is not our ambition to provide an exhaustive overview of market designs, policy interventions and behavioral traits which require MCP or other types of models, Tab. 6.1 lists some equilibrium problems treated in this text or encountered in the literature which cannot be directly solved using an optimization model. In addition, this table indicates for each of these problems why the equilibrium cannot directly be computed using an optimization model.

[16]This might imply that the solution is not technically feasible and hence redispatch is required.

Inherent assumption in optimization model which is violated	Market design	Policy intervention	Agent behavior
1. All variables contributing to a certain linking constraint participate in a paid-as-cleared-market	Net metering, Average price contracts [186]	Minimum price for green certificates, Feed-in tariffs [72], VAT tax	-
2. The endogenously determined market price cannot determine the value of variables not appearing in the corresponding linking constraint	Net metering, Average price contracts [186]	Grandfathering of emission allowances for new installations [184, 185]	-
3. All agents have the same valuation of the revenues from participating in the market represented by a linking constraint	-	-	Heterogeneous perception of uncertainties, Risk-averse investors [50, 185, 189]
4. The decision space of each agent is not dependent on endogenously determined market prices	-	-	Risk-averse investors [50, 185, 189]

Table 6.1: Examples of market designs, policy interventions and agent behavior which cannot be represented in optimization models. The inherent assumption made in optimization models which is violated in the presented examples is given in the first column. See Section 6.3.2 for a more detailed discussion regarding these inherent assumptions.

6.4.1 Minimum price for green certificates

Consider an equilibrium problem where a green certificate scheme is introduced to incentivize investments in renewable electricity generation. In this scheme, a fraction of the electricity sold by suppliers is obliged to come from renewable energy sources (RES). Generators are provided a green certificate for every unit of electrical energy generated by RES. These certificates can be sold in the market for green certificates in which the generators form the supply side and the electricity suppliers form the demand side. Assume further that in order to reduce uncertainties for investors in renewable electricity, generators are guaranteed a minimum price for their green certificates. More specifically, if the market price of the certificates (p^{GC}) is low, generators have the option to sell their certificates to the distribution system operator (DSO) which is obliged to buy these certificates at the guaranteed minimum price ($P_b^{GC,DSO}$). The DSO can in turn sell the certificates to the suppliers in the market (since the market price for green certificates in these moments is below the minimum price, the DSO will make a loss). This support system has among others been implemented in Belgium.

In this example, we focus on the long-run equilibrium between the different GenCos. The suppliers and the DSO are not explicitly represented in the problem formulation. Under the above assumptions, the optimization problem faced by a profit-maximizing, price-taking GenCo i is as follows:

$$\max_{cap_i, gen_{i,t}, q_i^{DSO}, q_i^{MAR}} \quad \sum_t (gen_{i,t} p_t^{el} \Delta_t) + q_i^{DSO} P^{GC,DSO} + q_i^{MAR} p^{GC})$$

$$- \Big(cap_i C_i^{INV} + \sum_t (gen_{i,t} VC_{i,t} \Delta_t) \Big) \tag{6.15}$$

$$s.t. \quad cap_i - gen_{i,t} \geq 0 \quad \forall t \tag{6.16}$$

$$\sum_t (R_i gen_{i,t} \Delta_t) - q_i^{DSO} - q_i^{MAR} \geq 0 \tag{6.17}$$

$$gen_{i,t} \geq 0 \quad \forall t \tag{6.18}$$

$$cap_i, q_i^{DSO}, q_i^{MAR} \geq 0 \tag{6.19}$$

The problem is very similar to the example presented in Section 6.3.1. For sake of simplicity, we again consider that every agent can only invest in a single technology. Aside from the revenues from selling their electricity in the market for electricity, the generators of renewable energy receive additional revenues by either selling their green certificates to the DSO or directly to the market. Here, q_i^{DSO} and q_i^{MAR} represent the number of certificates sold by agent i to the DSO and the market for green certificates respectively. Eq. (6.17) ensures that each agent cannot sell more certificates than those received by generating renewable electricity. In this equation, the parameter R_i represents the share of the electricity generated with a certain technology i which is considered to be renewable. In addition, there are now two linking constraints:

$$\sum_i (gen_{i,t}\Delta_t) = D_t\Delta_t \quad (p_t^{el}) \quad \forall t \tag{6.20}$$

$$\sum_i \sum_t (q_i^{DSO} + q_i^{MAR}) \geq FR \sum_t (D_t\Delta_t) \quad (p^{GC}) \tag{6.21}$$

Eq. (6.20) again states that total generation should equal the demand for electricity in every time step, whereas Eq. (6.21) guarantees that sufficient green certificates are generated for the suppliers to meet their obligation. We assume here that a fraction FR of all generated electricity should be generated by RES.

Defining an optimization problem which directly solves this equilibrium problem is not possible. This because the first assumption which is inherently made by optimization models is violated in this example (see Section 6.4.2). More specifically, not all variables appearing in the linking constraint which ensures a balance between the provision and the demand for green certificates (Eq. (6.21)) participate in a paid-as-cleared market for green certificates. Although the variables q_i^{DSO} and q_i^{MAR} both contribute equally to meeting the linking constraint for the supply of green certificates, the variable q_i^{DSO} does not receive the market price. Mathematically, the condition specified in Eq. (6.12) dictates that the objective function of the optimization problem faced by each GenCo i should contain a term $q_i^{DSO}p^{GC}$. Note that it thus not a problem that the variables q_i^{DSO} and q_i^{MAR} do not contribute equally to the objective function of the optimization problem of the GenCo. Rather, the problem is simply that the market price for green certificates does not apply to variable q_i^{DSO}[17].

6.4.2 Net metering

Consider an equilibrium problem where, in addition to the generators competing on the wholesale level, residential consumers j can decide to invest in solar PV panels. For sake of simplicity, we assume that all consumers have the option to invest in solar PV panels. We furthermore assume that all residential consumers have net metering contracts with their suppliers. The suppliers are not explicitly modeled, but we assume that these suppliers offer a single retail price $p_t^{el,RT}$

[17]It is thus possible to have the term $q_i^{DSO}(p^{GC} + A)$ in the objective function of each GenCo i. However, it is not possible to a priori introduce a correction factor A such that the condition $A + p^{GC} = P^{GC,DSO}$ is satisfied. It would be possible to define a parameterized surplus maximization problem, where the parameter A would be adapted in an iterative procedure until $A + p^{GC}$ converges to $P^{GC,DSO}$. However, the convergence might be an issue and would strongly increase the computational cost of solving the problem.

to all consumers/prosumers regardless of their consumption (and generation) patterns.

Each consumer j then faces the problem of minimizing its costs for electricity by deciding whether to buy all electricity via the suppliers or generate some electricity themselves by investing in solar PV panels:

$$\min_{cap_j^{PV}, gen_{j,t}^{PV}} \quad p^{el,RT} \sum_t \big((D_{j,t} - gen_{j,t}^{PV})\Delta_t\big) + C_j^{INV,PV} cap_j^{PV}, \tag{6.22}$$

$$s.t. \quad gen_{j,t}^{PV} \leq cap_j^{PV} CF_{j,t}^{PV} \quad \forall t, \tag{6.23}$$

$$cap_j^{PV}, gen_{j,t}^{PV} \geq 0. \tag{6.24}$$

Here, $gen_{j,t}^{PV}$ and $D_{j,t}$ are respectively the average electrical power generated and consumed by consumer j during time interval t. In addition, the parameter $CF_{j,t}^{PV}$ represents the capacity factor of the solar PV panels within this time interval.

The optimization problem faced by each GenCo i operating in the wholesale markets is as follows:

$$\max_{cap_i, gen_{i,t}} \quad \sum_t \Big(gen_{i,t}(p_t^{el,WS} - VC_i)\Delta_t\Big) - cap_i C_i^{INV} \tag{6.25}$$

$$s.t. \quad gen_{i,t} \leq cap_i \quad \forall t, \tag{6.26}$$

$$cap_i, gen_{i,t} \geq 0, \tag{6.27}$$

where $p_t^{el,WS}$ represents the average wholesale electricity price during time interval t.

The linking constraint representing the balance between supply and demand is as follows:

$$\sum_i gen_{i,t}\Delta_t + \sum_j gen_{j,t}^{PV}\Delta_t = \sum_j D_{j,t}\Delta_t \quad (p_t^{el,WS}) \quad \forall t. \tag{6.28}$$

For sake of simplicity we have assumed here that the total demand for electricity comes from residential consumers.

Finally, we assume that the retail price is determined by the suppliers as the volume weighted wholesale price of the net consumption of all consumers increased by a margin for suppliers (T^{supp}) and the transmission and distribution tariffs (T^{trans} and T^{distr}).

$$p^{el,RT} = \frac{\sum_{j,t}\big((D_{j,t} - gen_{j,t})p_t^{el,WS}\Delta_t\big)}{\sum_{j,t}\big((D_{j,t} - gen_{j,t})\Delta_t\big)} + T^{supp} + T^{trans} + T^{distr} \tag{6.29}$$

Defining an optimization problem which directly solves this equilibrium problem is not possible. This because the first assumption inherently made by optimization models is again violated in this example. Specifically, the net demand of residential consumers in a certain time step is not charged the paid-as-cleared wholesale market price (i.e., the dual variable of Eq. (6.28)). Assume for instance that the wholesale prices are very high during summer, while they are very low during winter and that there are two consumers who consume the same amount of electricity on an annual basis. The first consumer mainly consumes during the winter and the second consumer mainly consumes during summer. Given our assumptions regarding retail price formation, both consumers have the same incentives for investing in solar PV panels. However, in a surplus maximization model, the wholesale market clearing linking constraint Eq. (6.28) will implicitly determine that the consumer which mainly consumes during the summer would have to pay more for his electricity and hence has a higher incentive for investing in solar PV panels. As such, an optimization model cannot directly simulate the market distortion related to having average prices. Note that incorporating the margin for suppliers as well as the transmission and the distribution charges poses no problem as long as these additional charges are assumed to be independent of the market outcome (i.e., the market prices).

6.4.3 Decision making under uncertainty

In liberalized and deregulated electricity markets, GenCos face a lot of uncertainties. These include among others the uncertainty regarding future fuel prices, technological development, demand growth, policy interventions, and the decisions made by competitors [185, 15]. GenCos can account for these uncertainties in the investment planning problem by considering a number of possible scenarios, where each scenario represents one possible realization of the uncertain parameters.

Assuming risk-neutral GenCos, the objective of each GenCo i is to maximize its expected profits. Given a set of scenarios $w \in \Omega$, each with a probability of π_w, the objective function becomes:

$$\max_{cap_i, gen_{i,t,w}} \quad \sum_w \pi_w \Big[\sum_t \big(gen_{i,t,w} (p^{el}_{t,w} - VC_{i,w}) \Delta_t \big) - cap_i C_i^{INV} \Big]. \quad (6.30)$$

The market clearing constraint is now imposed for every time step and scenario.

$$\sum_i gen_{i,t,w} \Delta_t = D_{t,w} \Delta_t \quad (\pi_w p^{el}_{t,w}) \quad \forall t, w \quad (6.31)$$

As long as the expectations of the different agents towards the uncertain parameters are homogeneous (i.e., the probability that a certain realization of the uncertain parameters occurs is perceived to be the same by all agents), the stochastic equilibrium problem can be converted to a stochastic surplus maximization problem in which the objective function is to maximize the expected total surplus (as shown in [180]). Note that in such a stochastic surplus maximization problem, the dual variable of the linking constraint (Eq. (6.31)) can be interpreted as the probability-weighted electricity price, as indicated between brackets. Following the first necessary condition for an equilibrium problem to be cast in an optimization problem (Eq. (6.12)), the objective function of the GenCo should thus contain the terms $\sum_{t,w} gen_{i,t,w}\Delta_t \pi_w p^{el}_{t,w}$. As can be seen from Eq. (6.30), this is indeed the case in this example.

However, a first issue arises if the expectations of the agents towards the uncertain parameters are not homogeneous, i.e., when different agents attach a different probability to a particular scenario (e.g., one agent believes high carbon prices in the future are unlikely while another agent does not). In this case, an optimization model cannot be used to compute the equilibrium. This because different agents will have a different valuation of the revenue streams projected to result from a certain market in a certain scenario, which is not in line with the third inherent assumption made in optimization models (see Section 6.3.2).

A second issue arises if agents are assumed to be risk averse. Consider as an example that each GenCo aims to maximize their expected profits subject to the constraint that the potential loss cannot exceed a certain threshold T_i. The objective function of each agent remains to be represented by Eq. (6.30), but now each agent faces additional constraints:

$$\sum_t \big(gen_{i,t,w}(p^{el}_{t,w} - VC_{i,w})\Delta_t\big) - cap_i C_i^{INV} \geq -T_i \quad \forall w. \tag{6.32}$$

These constraints contain dual variables and hence cannot be represented directly in a surplus maximization problem, as indicated by Condition 2 in Section 6.3.2. A similar result can be found when more advanced risk measures such as the conditional value at risk are used to model risk-averse behavior. For a detailed treatment of risk in equilibrium problems, we refer to [185, 50, 189].

Most energy-system and power-system optimization models do not endogenously evaluate the uncertainty and the associated risk. Rather, an expectation of the involved risk is frequently reflected in the choice of the discount rate used. This discount rate then reflects both the cost of acquiring capital and a risk premium. Due to the fact that both the cost of acquiring capital and the involved risk can differ for different agents and different technologies/projects, the discount rates (i.e., the hurdle rates) used to evaluate the profitability of possible investments differs from project to project.

Given that different discount rates d_i are used for different projects, the objective function of the multi-period investment planning problem faced by GenCo i becomes:

$$\max_{cap_{i,y}, gen_{i,y,t}} \quad \sum_y \frac{1}{(1+d_i)^y} \Big(\sum_t \big(gen_{i,y,t} (p^{el,WS}_{y,t} - VC_{i,y}) \Delta_t \big) - cap_i C^{INV}_{i,y} \Big) \tag{6.33}$$

Here, the index y is added which represents different years in the planning horizon. For simplicity of notation, we again assume that each agent can invest only in a single technology, and that the discount rate is only dependent on the characteristics of the agent and the choice of technology.

Due to the fact that different agents apply different discount rates d_i, the value of generating a certain amount of electricity in a specific future time period is different for each agent despite the fact that there is a unique price for electricity in each period. This is similar to the issue encountered in the stochastic model with heterogeneous expectations detailed above. As a result, optimization models cannot be used to compute the equilibrium when different projects are evaluated using different discount rates[18]. For a detailed discussion of this issue, we refer to [51].

6.5 Summary and conclusions

In the context of liberalized and deregulated energy markets, long-term energy-system or power-system optimization models are used for two distinct purposes. A first is to address normative questions by analyzing how the optimal transition of the energy/electricity system looks like under certain assumptions. A second is to describe the likely/expected evolution of the energy/electricity system when certain policies are put into place (i.e., a descriptive perspective is taken). In this regard, optimization models rely on the fact that in perfectly competitive markets the surplus is maximized in the market equilibrium. As such, the market equilibrium can be computed by maximizing total surplus (at least, under the assumption of perfect competition).

While optimization models can be used to compute the market equilibrium in markets in which not all conditions for perfect competition are satisfied, there are a number of limitations for the use of optimization models. One well-known limitation is that optimization models implicitly assume price-taking agents. To

[18]Nevertheless most optimization models approximate the impact of varying discount rates by altering the capital costs of different technologies based on the assumed hurdle rates for the different technologies. As shown in [51], the accuracy of this approximation depends on how the projected revenues vary over the lifetime of the project.

analyze the equilibrium when agents behave strategically, other mathematical techniques have been used, such as mixed complementarity problems (MCPs), mathematical problems with equilibrium constraints (MPECs) and equilibrium problems with equilibrium constraints (EPECs). Even if all agents are assumed to be price takers, other market imperfections sometimes necessitate the use of such mathematical techniques. However, there is no general overview in the literature regarding the limitations of optimization models in representing specific market designs, policy interventions or behavioral characteristics of agents when all agents are assumed to be price takers.

In this chapter, we provided an overview of the limitations of optimization models for determining the market equilibrium. To this end, we have analyzed how a Nash equilibrium problem and a surplus maximization problem can both be formulated as an MCP. If it can be shown that the MCP formulation of a surplus maximization problem cannot be equivalent to the MCP formulation of the equilibrium problem, we can conclude that the equilibrium cannot be determined using an optimization model.

Using this methodology, two mathematical conditions for equilibrium problems with price-taking agents are derived which need to be satisfied in order for the equilibrium problem to be solved using an optimization problem. These two conditions are both related to duality.

The first condition relates to the double role of linking constraints (i.e., constraints which contain variables of multiple agents) in optimization models. These constraints first of all serve to impose physical or policy constraints which must be satisfied in the equilibrium (e.g., the balance between demand and supply of electricity). Second, in optimization models, these linking constraints implicitly represent the markets and determine how the variables appearing in these constraints are remunerated. As such, optimization models cannot distinguish between a physical or policy constraint on the one hand and the revenues and costs attached to the variables appearing in this constraint via the market implicitly formed around this constraint on the other hand. Due to the fact that these implicitly formed markets follow certain rules, this leads to three inherent assumptions made in optimization models:

1. all agents' variables contributing to a certain linking constraint participate in a paid-as-cleared market implicitly formed around this linking constraint;
2. the endogenously determined market price corresponding to a certain linking constraint does not directly influence the value of variables not appearing in this linking constraint;

3. all agents have the same valuation of the revenues or costs related to the participation in a certain market formed around a linking constraint.

If these assumptions do not hold in an equilibrium problem, an optimization model can hence not be used.

A second condition relates to the fact that the endogenously determined market prices are dual variables of the linking constraints in the optimization problem. These dual variables cannot appear in the primal problem formulation. From this, a fourth assumption is derived which needs to be satisfied in order for an optimization problem to be capable of determining the equilibrium:

4. the decision space of each agent is not constrained by the endogenously determined market prices.

Finally, we illustrated these limitations of optimization models by presenting three equilibrium problems which cannot be directly solved using an optimization model. More specifically, we provided an illustration of a policy intervention, a market design and agent behavior which could not be represented in an optimization model. A first illustration focused on the market distortion introduced by guaranteeing a minimum price for green certificates. A second illustration addressed the market imperfection of having net metering for residential consumers. A final illustration focused on the decision making of different agents under imperfect information.

Chapter 7

Conclusions

This chapter summarizes the main contributions and conclusions of this PhD dissertation and provides suggestions for further research.

7.1 Summary and conclusions

7.1.1 Long-term planning models

The work presented in this dissertation addresses long-term planning models. Such long-term planning models form valuable tools for policy makers. First, these models can be used from a normative/prescriptive perspective to provide information on the ideal transition pathway of the energy system. This information can be used by policy makers to develop a long-term vision of the transition of the energy system and to set certain long-term objectives (e.g., the greenhouse gas emission reductions one wants to achieve in different energy sectors by a certain year). Second, long-term planning models can be used from a descriptive perspective to analyze likely transition pathways whenever certain policies are put into place. This allows policy makers for instance to assess the adequacy of certain policy measures to achieve the desired objectives.

Chapter 2 has presented a categorization of different types of long-term planning models. Two criteria were used to categorize planning models. A first criterion relates to the model scope. In this regard, a distinction was made between integrated assessment models, energy-economy models, energy-system planning models and power-system planning models. The second criterion relates to the methodology used to generate the transition pathways. Here, a distinction was made between computable general equilibrium models, optimization models, equilibrium models, system-dynamics models and agent-based models.

In this dissertation, the focus has been specifically on energy-system optimization models (ESOMs). These are bottom-up models which typically focus on the evolution of the entire energy system in a single or multiple countr(y)(ies), over a time horizon of 20-100 years. The term bottom-up refers to the fact that these models explicitly consider a high number of technology-types and describe the energy-system as an interlinkage of these different technology-types. As such, these models are capable of generating detailed and coherent transition pathways for the energy system by capturing the complex inter-sectoral, inter-temporal and inter-regional interactions. Although the findings and methods developed in this dissertation are mainly envisioned to be applied to improve the modeling of the electrical power sector within ESOMs, the simulations and analyses presented in this disseration are based on using models which restricted their the scope to the electrical power system (i.e., power-system optimization models (PSOMs)).

7.1.2 Capturing the challenges related to the integration of intermittent renewable energy sources

Due to the large scope and the high level of technological detail in ESOMs, solving these models quickly becomes computationally demanding. To limit the computational cost, low levels of temporal and technical detail are typically used. However, in the context of an increasing penetration of strongly fluctuating and limitedly predictable renewable energy sources such as wind turbines and solar PV panels, this low level of temporal and technical detail might not be sufficient to grasp the challenges related to integrating these intermittent renewable energy sources (IRES).

Impact of the low level of temporal and technical detail

Chapter 3 has analyzed the impact of using a low level of temporal and technical detail in ESOMs for a varying penetration of IRES.

First of all, this chapter has provided an overview of the level of temporal and technical detail typically employed in ESOMs. Regarding the temporal detail, ESOMs typically represent seasonal and daily variations in demand and supply by using 4-48 so-called time slices. The demand for electricity in each time slice is then determined by taking the average value of that part of the electricity demand time series which corresponds to that time slice (e.g., all hours corresponding to winter nights). A similar approach is taken to restrict the amount of electricity that can be generated by IRES in each time slice. In terms of the technical detail, ESOMs operate on a technology-type level and do typically not consider individual electrical power generation units and the technical constraints they face when cycling, i.e., changing the power output or the on/off state. In addition, ESOMs generally do not consider system-wide constraints such as the need for operating reserves to deal with contingencies or forecast errors.

Second, an assessment regarding the impact of the low level of temporal and technical detail was presented for a case study loosely based on the Belgian electrical power system. **Both the low level of temporal and technical detail used in ESOMs were shown to lead to an overestimation of the uptake of IRES, an overestimation of the electricity that can be generated by baseload technology-types and an underestimation of the operational costs for power generation.** While this impact was observed to be limited for low penetrations of IRES, it became significant as the penetration of IRES increased. **For high penetrations rates of IRES** of about 35-50% of annual electric energy generation, **the impact of the low level of temporal detail was shown to have a considerably higher impact than the low level of technical detail employed.**

We therefore recommend prioritizing improving the temporal representation in ESOMs. The high impact of the low level of temporal detail was shown to result from the fact that traditional time-slicing methods lead to smoothing of the variability of IRES by averaging the instantaneous electrical power generation.

Improved time-slicing methods

Chapter 4 has focused on developing improved time-slicing methods.

First, this chapter has presented a number of fundamentally different methods for time slicing and has briefly evaluated their ability to capture the variability of IRES. A first finding is that traditional time-slicing methods, which disaggregate a year into a number of time slices representing different seasons, days of the week and/or diurnal periods, and use the average electricity generation of IRES corresponding to these time slices, are not capable of capturing the variability of IRES, and hence perform poorly for moderate to high penetrations of IRES, even if a relatively high number of time slices are used. A second finding is that two, very **different, time-slicing methods are capable of drastically improving the accuracy of ESOMs, even if a low number of time slices**

is used (e.g., 12). A first time-slicing method, labeled the 'enhanced integral' time-slicing method, does no longer consider specific seasons or diurnal periods to define the time slices. Rather, time series of an entire year are sliced based on the demand level and the resource availability of IRES. As such, the averaging of those parts of the time series corresponding to a specific time slice does not smooth the power generation of IRES as much. The main drawback of this time-slicing method is that the chronology is not preserved, which makes it difficult to assess the value of/need for different flexibility options (e.g., energy storage technology-types) to deal with short-term and longer term variations in demand and supply. A second time-slicing method avoids averaging of IRES generation output by directly using the data of a small number of representative historical periods (e.g., days) rather than slicing the time series of an entire year. This approach was shown to achieve similarly good results as the enhanced integral time slicing method in terms of capturing the variability of IRES, but has the additional advantage that the chronology is retained (at least, within the representative periods). However, the quality of the representative periods approach is strongly dependent on the ability to select a representative set of historical periods.

The remainder of Chapter 4 has focused on approaches for selecting such a representative set of historical periods. To this end, **a novel optimization-based approach and a derived hybrid approach for selecting representative periods have been developed**. The results provided by these approaches were compared to the results from different approaches available in the literature. **The developed approaches were shown to be more accurate than the approaches available from the literature**. The significance of a better selection of representative periods is that with the same number of time slices, a higher accuracy can be obtained. Similarly, to achieve a certain accuracy, a better selection of representative days allows reducing the number of time slices. For instance, the accuracy obtained when selecting 2 representative days using the developed optimization-based approach was shown to be similar to the accuracy obtained when selecting 8 representative days using the more advanced approaches from the literature.

Finally, the **impact of the temporal resolution** when representative days are used has been analyzed. The results of this analysis indicated that **if only a low number of time slices (e.g., 12 to 72) can be used, it is better to use a low resolution (e.g., 4-hourly) and increase the number of representative days**. Whenever more time slices can be used, the resolution can be increased, but an hourly resolution was shown to only become worthwhile whenever more than 288 time slices are used.

Incorporating technical constraints

Chapter 5 has focused on increasing the technical detail in ESOMs.

The first objective of this chapter has been to determine the significance of incorporating detailed technical constraints in ESOMs. To address this question, a PSOM which integrates clustered unit commitment (CUC) constraints has been developed. For a variety of scenarios and cases, the results of the planning model which incorporated these CUC constraints were compared to a model version which did not incorporate technical constraints. The presented results indicate that **for the majority of the considered scenarios and cases, neglecting technical constraints has only a limited impact on both the projections of the system cost and the capacity mix. The main exception relates to investments in electrical storage technology-types, which were shown to increase significantly whenever technical constraints were considered.**

We therefore conclude that if the focus is not on electrical storage technology-types or other dedicated flexibility providers, incorporating technical constraints is not essential.

The second objective of this chapter has been to **develop reduced formulations of the CUC constraints which could be tractably integrated in ESOMs and PSOMs**. A first step in this regard was to analyze to what extent and how specific constraints impact the model results. This analysis has provided information regarding which constraints could be omitted and how certain constraints could be simplified while still capturing the main impact of these constraints. This information was leveraged to derive different reduced formulations of the CUC constraints. The results of the planning models which integrated these reduced formulations were evaluated with respect to the planning model integrating the original CUC constraints, which served as a reference. Our results indicate that some of these reduced formulations are highly accurate, both in terms of projections of the total system cost and in terms of the obtained capacity mix. Even more so, the errors introduced by using these reduced formulations instead of the original CUC constraints were shown to be significantly smaller than the differences in model results stemming from the choice of the cycling capabilities of thermal power plants, given the large range of reported cycling capabilities.

We therefore conclude that the developed reduced formulations are more than sufficiently accurate. In terms of computational cost, these reduced formulations were shown to be capable of reducing the computational cost by a factor of 5 to 600 for the different simulations.

Finally, this chapter has highlighted that there is a risk that the incorporated technical constraints are overly and unrealistically restrictive, which can lead to strong overestimations of the projected system costs and suboptimal penetration levels of IRES. This was shown to occur if stringent assumptions are taken regarding the cycling capabilities of thermal power plants and no other sources of flexibility are explicitly considered. Under these assumptions, the difficulty of providing the operating reserve requirements was shown to be the key factor. A review of the literature has furthermore revealed that big differences exist between different planning models in terms of the sizing of these reserve requirements and that the sizing of these reserve requirements is typically based on simplified rules which typically cannot be extrapolated to systems with very high penetration levels of IRES.

We therefore conclude (i) to be highly cautious when incorporating reserve requirements in planning models and (ii) that whenever reserve requirements are incorporated in planning models, it is essential to consider different sources of flexibility and how these can contribute to the provision of reserves.

7.1.3 Representing markets, policy interventions and agent behavior

Descriptive scenarios aim to describe the likely evolution of the energy system under certain assumptions regarding the policy framework, fuel cost evolutions, technological evolution, etc. Since (i) in liberalized electricity markets, the decision to invest in generation assets are made by private companies which aim to maximize their profits and (ii) these investment decisions are influenced by the market design and the policy framework, ESOMs should ideally be capable of representing the decision making of private companies as well as the incentives provided by specific market designs and policies. However, as discussed in Chapter 2, optimization models do not explicitly consider different agents or markets. Rather, optimization models rely on economic theory stating that under perfect competition, total surplus is maximized in the market equilibrium. Hence, by maximizing the total surplus, the equilibrium can be computed.

Chapter 6 has analyzed the possibilities and limitations of optimization models to represent different market designs, policy interventions and behavioral characteristics of different agents. Since it is well-known that optimization models cannot represent strategic behavior, the focus was restricted to problems with price-taking agents.

Two conditions were derived which need to hold in order to be able to cast an equilibrium problem into an optimization problem. Both conditions can be ascribed to duality theory. A first condition relates to the double role of linking constraints (i.e., constraints which contain decision variables of multiple agents such as a constraint ensuring the balance between supply and demand of electricity). These constraints first of all ensure that physical or political constraints are satisfied. Second, in optimization models, these constraints also implicitly represent the markets, i.e., which agents participate in these markets and how these agents are remunerated for participating in these markets. Optimization models hence cannot distinguish between a physical or political constraint, on the one hand, and the revenues and costs attached to the variables appearing in this constraint via the market implicitly formed around this constraint, on the other hand. A second condition relates to the fact that dual variables cannot appear in the primal problem formulation of optimization models. From these two conditions, four inherent assumptions made in optimization models were postulated. If one or more of these assumptions does not hold for a certain equilibrium problem, an optimization model cannot be used directly to determine the equilibrium. These assumptions are the following:

1. all agents' variables contributing to a certain linking constraint participate in a paid-as-cleared market implicitly formed around this linking constraint;
2. the endogenously determined market price corresponding to a certain linking constraint does not directly influence the value of variables not appearing in this linking constraint;
3. all agents have the same valuation of the revenues or costs related to the participation in a certain market formed around a linking constraint;
4. the decision space of each agent is not dependent on the endogenously determined market prices.

The corresponding limitations of optimization models have been illustrated by presenting three relevant equilibrium problems which cannot be solved directly by solving an optimization problem.

7.2 Suggestions for further research

7.2.1 Capturing the challenges related to the integration of intermittent renewable energy sources

Improved time-slicing methods

In this PhD dissertation, it was shown that two advanced time-slicing methods can limit or avoid the smoothing of IRES generation and hence allow capturing key elements of the challenges related to integrating IRES. However, in this work, the focus was restricted to simplified electrical power systems resembling a single country. Applications of these advanced time slicing methods to models with multiple regions and or multiple energy sectors will likely reveal additional challenges meriting further research.

We have stated that one of the advantages of the time-slicing method based on selecting a number of representative historical periods is that the chronology within each representative period is retained, which is essential for incorporating certain technical constraints as well as for assessing the value of storage technology-types and active demand response. However, a first limitation of the presented approach for selecting representative days is that no criterion was formulated to determine the representativeness of a set of representative periods in terms of their arbitrage potential. Second, aside from performing arbitrage within each representative period, storage technology-types capable of storing large amounts of energy could get additional value by arbitraging over longer periods, i.e., between different representative periods. As presented in the model formulation in Chapter 5, it is possible to link sequential representative periods to allow arbitraging between them. However, in our model formulation it has been assumed that each representative period is repeated a number of times before the next representative period begins. Especially when a low number of representative periods are used (which necessitates more repetitions per representative period), this might lead to underestimations of the longer-term arbitrage potential. To conclude, the impact of the use of representative periods on investments in electrical storage technology-types merits further research. Both in the selection of the representative periods, and in the linking of the different representative periods, opportunities exist for better approximating the value of storage technology-types.

Finally, our results have shown that using a high temporal resolution only becomes worthwhile if a high number of time slices can be used. Further research is needed to assess the generality of this conclusion. Furthermore, given that the majority of ESOMs cannot use a high number of time slices and hence would better use a low resolution, development of efficient approaches to reduce the temporal resolution could further increase the accuracy of the representative periods approach. In our research, the resolution was simply reduced by dividing a representative periods in blocks of the same duration (e.g., 4 hours).

Incorporating technical constraints

Our research has shown that the technical constraints faced by thermal power plants can be accurately represented using reduced formulations of the CUC constraints which can be tractably integrated in planning models. However, there is a significant amount of uncertainty regarding the system needs, and a large range of cycling capabilities of thermal power plants are reported. Therefore, we suggest that further research should prioritize clearly identifying the system needs and the cycling capabilities of power plants rather than focusing on the formulation of the constraints faced by thermal power plants.

In terms of the system needs, the presented review of the operating reserve requirements in different planning models has highlighted that, between different planning models, significant differences exist in terms of the sizing of reserves as well as the required activation times for different types of reserves. In addition, we have shown that the sizing of reserves is typically based on simple rules which cannot be extrapolated to systems with high shares of IRES. The endogenous sizing of operating reserves in planning models hence merits further research.

In addition, as the power generation of IRES displaces the power generation of thermal power plants, the amount of spinning, synchronized generators is reduced with an increasing penetration of IRES. During some moments, this might reduce the inertia of the system up to the point where thermal generators need to be kept online to ensure a minimum level of inertia needed to maintain a stable system. Such constraints were not considered in this dissertation but can possibly impact the dispatch and the system costs in systems with high IRES penetrations. Therefore, the need for inertia and options to mitigate this need for inertia are an interesting topic for further research.

Regarding the supply of these system services, further research opportunities exist for modeling the abilities of different flexibility providers such as storage technology-types and active demand response to provide these services.

ESOMs also typically consider a planning reserve margin to ensure generation adequacy. These planning reserve margins are particularly needed when very few time slices are used and no detailed reserve requirements are incorporated. The capacity credit of different IRES and storage technology-types, i.e., their ability to contribute to meeting this planning reserve margin, is typically assumed to be constant over the considered time horizon. However, the actual capacity credit is strongly dependent on the load profile and IRES profiles as well as the penetration level of IRES. The endogenous determination of the capacity credit of different technology-types can be an interesting topic for future research.

Finally, in this dissertation network constraints have not been considered. ESOMs typically consider trade-based network constraints. The relevance of incorporating more detailed network constraints, such as DC load flow constraints, merits further research. Given that there is an ongoing evolution towards a more decentralized electricity system, also detailed distribution network constraints can become more relevant to consider.

7.2.2 Representing markets, policy interventions and agent behavior

As discussed in this work, ESOMs cannot exactly represent certain behavioral characteristics, market designs and policy interventions. First, assessing the relevance of some of these elements such as risk-averse behavior, lack of real-time pricing and net metering schemes for long-term planning purposes is an interesting topic for further research.

Second, other modeling methodologies such as equilibrium models provide more opportunities for reflecting specific market designs and behavioral characteristics. However, these models have rarely been applied for long-term planning, even though the solvers and solution techniques for this type of problems have lately been drastically improved. Further research into the possibilities of using equilibrium models, e.g., formulated as mixed complementarity problems (MCPs), for long-term planning purposes is hence required.

7.2.3 Accounting for long-term uncertainties

Recently, a lot of attention has gone to capturing the variability and limited predictability of IRES in the short-term. However, given the huge uncertainties faced on the longer term regarding, for instance, fossil fuel prices, technological evolution and the policy framework, an interesting topic for future research is to account for these long-term uncertainties to derive robust policy recommendations.

Appendix A

Economic and technical data of power generation technologies considered in Chapter 3

[-1] Fuel prices for nuclear plants are expressed in [EUR/MWh$_e$] and include front-end and back-end costs of the nuclear fuel cycle. Efficiencies for these plants are adjusted to correspond to the fuel prices.

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Technology	Investment cost $[\frac{kEUR}{kW_e}]$				FOM $[\frac{EUR}{(kW_e a)}]$				VOM $[\frac{EUR}{MWh_e}]$	Life time $[a]$	Lead time $[a]$
	2010	2020	2030	2050	2010	2020	2030	2050			
NUC	3.66	3.66	3.66	3.66	0	0	0	0	11.1	60	7
COAL SC	1.71	1.71	1.71	1.71	34	34	34	34	6	35	4
CCGT	0.86	0.86	0.86	0.86	26	21	20	20	5	25	2
OCGT	0.49	0.49	0.48	0.47	12	12	12	12	4	15	2
Onsh. Wind	1.40	1.27	1.19	1.11	34	27	24	21	-	25	1
Offsh. Wind	4.30	3.40	2.70	2.10	130	95	75	60	-	25	1
Sol. PV	3.66	1.42	1.14	0.78	51	16	13	-	10	30	1

Table A.1: Economic characteristics of the considered technologies in Chapter 3. Data is taken from [111]-[119].

Technical characteristic		NUC	COAL SC	CCGT	OCGT
Efficiency [%]1	2010	100	45	58	39
	2020	100.1	46	60	39
	2030	102	49	62	40
	2050	104	49	64	41
MSOP [%/P_{nom}]		50	50	50	10
Eff. loss at MSOP [%pt]		-	2	8	21
Ramp rate [%P_{nom} /min]		5	4	7	17.5
Ramp cost [EUR/ ΔMW]		0	1.3	0.25	0.25
MUT [h]		24	6	4	1
MDT [h]		48	4	1	1
Start-up energy [$MWh_{th}/\Delta MW_e$]		17	5.7	1.7	0.0
Start-up depreciation [EUR/ΔMW_e]		1.7	5	10	10
Availability [%]		85	85	85	85

Table A.2: Cycling characteristics of the considered dispatchable technologies in Chapter 3. The efficiency, MSOP, efficiency loss at this MSOP, ramping capabilities and corresponding costs, minimum up and down times (MUT/MDT), start-up fuel consumption and depreciation costs as well as annual availability are presented.

Price [EUR_{2008}/MWh_p]	2010	2020	2030	2040	2050
Coal	8.81	9.44	9.79	10.33	10.82
Natural gas	23.89	24.30	25.12	25.66	26.27
Uranium[1]	6.34	6.34	6.34	6.34	6.34
Price [$EUR_{2008}/tonCO_2^{eq}$]					
GHG emissions	0	12.5	25	37.5	50

Table A.3: Fuel and GHG emission prices considered in Chapter 3.

Appendix B

Economic and technical data of power generation technologies considered in Chapter 5

Technology	Investment cost $[\frac{kEUR}{kW_e}]$	FOM $[\frac{EUR}{(kW_e a)}]$	VOM $[\frac{EUR}{MWh_e}]$	Life time $[a]$	Lead time $[a]$	Efficiency [%]	Availability [%]
NUC	5.00	42	5	50	7	36	85
COAL SC	1.70	33	6	35	4	49	85
COAL SC CCS	2.02	34	20	35	5	40	85
CCGT	0.86	20	4	25	2	64	85
CCGT CCS	1.09	39	10	25	3	53	85
OCGT	0.57	17	4	15	2	45	85
Onsh. Wind	1.11	21	-	25	1	-	-
Offsh. Wind	2.10	60	-	25	1	-	-
Sol. PV	0.78	12	-	30	1	-	-

Table B.1: Economic characteristics of the considered thermal and renewable technologies in Chapter 5. The VOM costs of the CCS technologies include capture and transportation costs. Data is taken from [111]-[119].

Characteristic	PHS	BESS
Investment cost power $[\frac{kEUR}{kW_e}]$	1.15	-
Investment cost energy $[\frac{kEUR}{MWh}]$	98.2	337.4
FOM $[\frac{EUR}{(kW_e a)}]$	3.4	16.9
VOM $[\frac{EUR}{MWh_e}]$	5	-
Life time $[a]$	80	10
Lead time $[a]$	4	2
Round-trip Efficiency [%]	75	90
Availability [%]	97	97
Minimum discharge duration $[h]$	4	1
Maximum discharge duration $[h]$	16	1

Table B.2: Economic characteristics of the considered storage technologies in Chapter 5. The reported efficiencies correspond to the round-trip efficiency. Data is taken from [111],[119],[160].

Technical characteristic	PHS	BESS
MSOP while pumping $[\%/P_{nom}]$	60	0
MSOP while turbining $[\%/P_{nom}]$	30	0
Ramp rate $[\%P_{nom}$ /min]	20	100
Start-up time charging [min]	15	0
Start-up time discharging [min]	5	0
Shut-down time charging [min]	5	0
Shut-down time discharging [min]	10	0

Table B.3: Cycling characteristics of the energy storage technologies. Data is taken from [160, 119].

Fuel	Coal	Natural gas	Uranium
Price $[EUR_{2008}/MWh_p]$	23.3	32.2	3

Table B.4: Fuel prices considered in Chapter 5.

Appendix C

Mathematical formulation for the improved sizing of VRFER and the provision of upward reserves by IRES

This appendix contains the mathematical formulation for the sizing of variable renewable forecast error reserves (VRFER) dependent on the effective exposure to forecast errors and for the provision of upward reserves by intermittent renewable energy sources (IRES), as discussed in Section 5.4.3 of Chapter 5. In the remainder of this discussion, we focus on wind. However, the methodology can be directly transferred to other IRES. It must be noted that the presented formulation is highly simplified. It merely serves to get an idea of how results might change whenever the sizing of reserves is directly based on the exposure to forecast errors and IRES are allowed to provide upward reserves to cope with other types of uncertainty.

We make the base assumption that a certain fraction $(1-\alpha)$ of the forecasted wind power $\overline{W}$ can be guaranteed with a reasonable certainty. Following this assumption, the exposure to wind forecast errors is reduced whenever there is more curtailment, as visualized in Fig. C.1. In addition, in periods of strong oversupply of wind, the scheduled wind generation might be below the level which can be guaranteed with reasonable certainty. In this case, there is no need to ensure reserves to deal with wind forecast errors. Moreover, the curtailment below the wind generation level which can be guaranteed with reasonable certainty can be used to provide upward reserves to cover other sources of uncertainty. This is visualized in Fig. C.2.

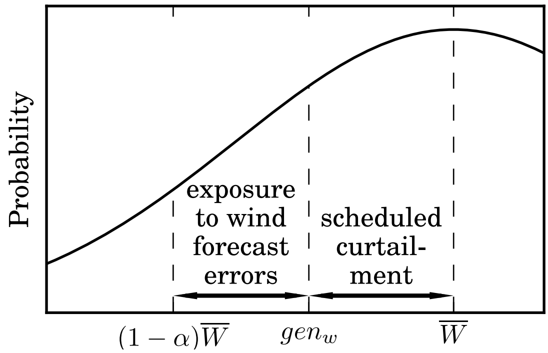

Figure C.1: Illustration of the reduction of the need for VRFER by scheduled curtailment. A probability distribution of wind generation is presented. The forecasted wind generation when there would be no curtailment is indicated by $\overline{W}$. The wind generation that can be guaranteed with a reasonable certainty is indicated by $(1-\alpha)\overline{W}$, where α represents the uncertain fraction of the forecasted wind generation. The scheduled wind generation is indicated by gen_w.

In the model, additional variables are needed to distinguish between IRES generation within the range that can be guaranteed with a reasonable certainty, and IRES generation on top of the level that can be guaranteed with reasonable certainty. The original equation (Eq. (5.33)) is now replaced by following set of equations and inequalities:

$$gen_{gr,p,t} + curt_{gr,p,t} = cap_{gr} CF_{gr,p,t} \quad \forall gr \in \mathcal{GR}, p \in \mathcal{P}, t \in \mathcal{T}, \tag{C.1}$$

$$gen_{gr,p,t} = gen^{certain}_{gr,p,t} + gen^{uncertain}_{gr,p,t} \quad \forall gr \in \mathcal{GR}, p \in \mathcal{P}, t \in \mathcal{T}, \tag{C.2}$$

$$gen^{certain}_{gr,p,t} \leq cap_{gr} CF_{gr,p,t}(1-\alpha_{gr}) \quad \forall gr \in \mathcal{GR}, p \in \mathcal{P}, t \in \mathcal{T}, \tag{C.3}$$

$$gen^{uncertain}_{gr,p,t} \leq cap_{gr} CF_{gr,p,t}\alpha_{gr} \quad \forall gr \in \mathcal{GR}, p \in \mathcal{P}, t \in \mathcal{T}, \tag{C.4}$$

In line with Fig. C.1, the required amount of operating reserves to deal with IRES forecast errors corresponds to $gen^{uncertain}_{gr,p,t}$. This is adapted for in Eq. (5.14)-(5.15).

The provision of upward reserves by IRES is restricted by the difference between the generation level that can be guaranteed with a reasonable certainty and the

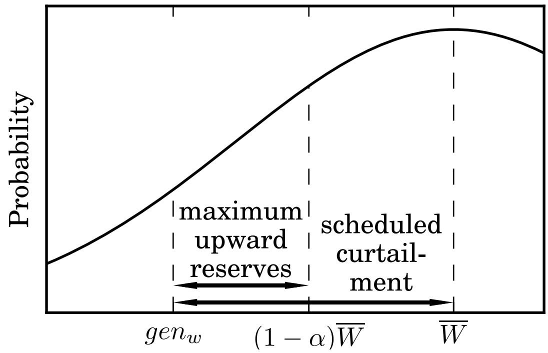

Figure C.2: Illustration of the provision of upward reserves by IRES. A probability distribution of wind generation is presented. The forecasted wind generation when there would be no curtailment is indicated by $\overline{W}$. The wind generation that can be guaranteed with a reasonable certainty is indicated by $(1-\alpha)\overline{W}$, where α represents the uncertain fraction of the forecasted wind generation. The scheduled wind generation is indicated by gen_w.

scheduled generation (see Fig. C.2):

$$\sum_{r\in\mathcal{R}} r^{+}_{r,gr,p,t} \leq cap_{gr} CF_{gr,p,t}(1-\alpha_{gr}) - gen^{certain}_{gr,p,t} \quad \forall gr \in \mathcal{GR}, p \in \mathcal{P}, t \in \mathcal{T}, \tag{C.5}$$

Additional constraints are needed to avoid that reserves are provided whenever the total generation of an intermittent generation source is effectively below the level that can be guaranteed with a reasonable certainty. Up to now, the model allows reducing $gen^{certain}_{gr,p,t}$ at the expense of increasing $gen^{uncertain}_{gr,p,t}$. As such, upward reserves could be provided to any type of upward reserve. This comes at the expense of increasing the demand for operating reserves to cope with forecast errors (since $gen^{uncertain}_{gr,p,t}$ is increased). However, depending on the required activation time used, these VRFER might be less expensive than other types of reserves. For this reason, additional constraints are incorporated, which only allow the provision of upward reserves by IRES whenever the total IRES generation level is below the level that can be guaranteed with a reasonable accuracy (or thus, whenever $gen^{uncertain}_{gr,p,t} = 0$). To this end, an additional binary variable $z_{gr,p,t}$ is introduced which indicates whether the upward reserves can be provided by IRES:

$$r^{+}_{r,gr,p,t} \leq M z_{gr,p,t} \quad \forall r \in \mathcal{R}, gr \in \mathcal{GR}, p \in \mathcal{P}, t \in \mathcal{T}, \tag{C.6}$$

$$gen^{uncertain}_{gr,p,t} z_{gr,p,t} = 0 \quad \forall gr \in \mathcal{GR}, p \in \mathcal{P}, t \in \mathcal{T} \tag{C.7}$$

, where M represents a very big number. However, the latter constraint is non-linear. Two additional constraints and an additional binary variable $y_{gr,p,t}$ are introduced to replace the latter constraint and avoid the non-linearity:

$$z_{gr,p,t} \leq y_{gr,p,t} \quad \forall gr \in \mathcal{GR}, p \in \mathcal{P}, t \in \mathcal{T}, \tag{C.8}$$

$$gen^{uncertain}_{gr,p,t} \leq (1 - y_{gr,p,t}) cap_{gr} CF_{gr,p,t} \alpha_{gr} \quad \forall gr \in \mathcal{GR}, p \in \mathcal{P}, t \in \mathcal{T}. \tag{C.9}$$

Whenever $y_{gr,p,t}$ is equal to one, Eq. (C.9) forces $gen^{uncertain}_{gr,p,t}$ to 0. In this case, $z_{gr,p,t}$ can be set to 1, and upward reserves can be provided. In contrast, whenever $gen^{uncertain}_{gr,p,t}$ does not equal 0, Eq. (C.9) forces $y_{gr,p,t}$ to be 0, which according to Eq. (C.8) ensures that $z_{gr,p,t}$ equals zero. Finally, via Eq. (C.6), this implies that no upward reserves can be provided.

Appendix D

Computational performance of the model variants proposed in Chapter 5

Tab. D.1 provides an overview of how the model variants with different levels of technical detail proposed in Chapter 5 reduce the problem size and the computation times.

Model variant	# Eq.	# Var.	# Discr. var.	Comp. time	Speed-up
REF	249,864	212,385	56,448	1,354.7	-
RELAXED	248,520	212,385	0	76.6	18
STRIPPED	180,071	153,248	0	14.5	93
REDUCED	171,959	153,248	0	10.4	131
SIMPLE	147,862	129,055	0	5.0	271
MO	22,869	26,910	0	0.47	1201

(a) cases without storage

Model variant	# Eq.	# Var.	# Discr. var.	Comp. time	Speed-up
REF	357,412	295,741	75,264	2,039.5	-
RELAXED	356,068	295,741	0	93.7	22
STRIPPED	255,363	212,412	0	39.0	52
REDUCED	241,875	209,724	0	31.6	65
SIMPLE	212,418	182,843	0	13.2	154
MO	49,793	43,066	0	3.2	630

(b) cases with storage

Table D.1: Overview of the problem size and the computational performance of the model variants with different levels of technical detail in the cases without storage (a) and with storage (b). The number of equations, variables and discrete variables as well as the average computation time and speed-up are presented. The number of equations and variables presented corresponds to scenarios A, C and D. In scenario B, these values are slightly lower as the nuclear technology is excluded in this scenario. Computation times are expressed in seconds and speed-ups are expressed relative to the reference (REF) model.

Appendix E

Integrability of inverse demand functions with cross-price elasticities

Assume a multi-commodity model with two commodities a and b. The commodities a and b can represent different commodities or commodities in different time steps. The inverse demand functions $f_{d,a}^{-1}(q_a, q_b)$ and $f_{d,b}^{-1}(q_a, q_b)$ for commodity a and b are both a function of q_a and q_b. For the surplus maximization model, a consumer value function should be created, which in this case is dependent on the consumption of both commodities a and b: $CV(q_a, q_b)$. Assume further that the supply functions for both commodities are indepdent of the consumption of the other commodity: $f_{s,a}^{-1}(q_a)$ and $f_{s,b}^{-1}(q_b)$. The objective function of the surplus maximization problem is than as follows:

$$TS(q_a, q_b) = CV(q_a, q_b) - \int_0^{q_a} f_s^{-1}(q_a')dq_a' - \int_0^{q_b} f_s^{-1}(q_b')dq_b'. \tag{E.1}$$

In the optimal solution of this optimization problem, the following conditions must hold:

$$\frac{\partial TS(q_a, q_b)}{\partial q_a} = 0, \tag{E.2}$$

$$\frac{\partial TS(q_a, q_b)}{\partial q_b} = 0, \tag{E.3}$$

By substituting Eq. (E.1) in Eq. (E.2)-(E.2), the latter equations can be expressed as:

$$\frac{\partial CV(q_a, q_b)}{\partial q_a} = f_{s,a}^{-1}(q_a), \tag{E.4}$$

$$\frac{\partial CV(q_a, q_b)}{\partial q_b} = f_{s,b}^{-1}(q_b). \tag{E.5}$$

On the other hand, in the equilibrium the willingness to pay for a certain commodity should equal the willingness to produce, or thus:

$$f_{d,a}^{-1}(q_a, q_b) = f_{s,a}^{-1}(q_a), \tag{E.6}$$

$$f_{d,b}^{-1}(q_a, q_b) = f_{s,b}^{-1}(q_b). \tag{E.7}$$

Hence, in order for the optimal solution (Eq. (E.4)-(E.5)) of the optimization problem to represent the equilibrium (Eq. (E.6)-(E.7), the following conditions must hold in the equilibrium:

$$\frac{\partial CV(q_a, q_b)}{\partial q_a} = f_{d,a}^{-1}(q_a, q_b) \tag{E.8}$$

$$\frac{\partial CV(q_a, q_b)}{\partial q_b} = f_{d,b}^{-1}(q_a, q_b) \tag{E.9}$$

Finally, by taking the partial derivative of all terms in Eq. (E.8) towards q_b, the partial derivative of all terms in Eq. (E.9) towards q_a, and noticing that the left hand sides of the resulting equations become identical, we can finally derive the following condition for the inverse demand functions:

$$\frac{\partial f_{d,a}^{-1}(q_a, q_b)}{\partial q_b} = \frac{\partial f_{d,b}^{-1}(q_a, q_b)}{\partial q_a}. \tag{E.10}$$

This condition thus states that the demand functions must be symmetric.

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Short curriculum

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Work experience:

2013-2017	Research assistant at KU Leuven, Mechnanical Engineering, Division of Applied Mechanics and Energy Conversion. Research at the doctoral level.

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2006-2009	Bachelor in de ingenieurswetenschappen: werktuigkunde-elektrotechniek, KU Leuven. *Cum Laude.*

List of publications

Articles in peer-reviewed academic journals

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